**REPORT**

Reimagine tomorrow.

# Duke Carolinas 2016 Power Manager Evaluation

April 11, 2017

**Principal authors:**

Josh Bode, M.P.P.
Candice Potter, M.S.
Ankit Jain, M.P.P.
Greg Sidorov, M.S.
Trevor Cummings, M.S.
Rachel Flaherman, B.S.

## Abstract

This study analyzes the impact of Duke Energy Carolina's Power Manager program on electricity demand for a range of weather conditions, dispatch hours, and load control strategies. Power Manager is a voluntary demand response program that provides incentives to residential customers who allow Duke Energy to reduce the use of their central air conditioner's outdoor compressor and fan on summer days with high energy usage. A key objective of the 2016 evaluation was to quantify the relationship between demand reductions, temperature, hour of day, and cycling strategy—referred to as the time temperature matrix. By design, a large number of events were called under different weather conditions, for different dispatch windows, using various cycling strategies so that demand reduction capability could be estimated for a wide range of operating and planning conditions. Duke Energy Carolinas uses the program's emergency load shed capability for a 102˚F day for planning. While emergency operations are rare and ideally avoided, they represent the full demand reduction capability of Power Manager. If 100% emergency shed becomes necessary on a 102˚F day, Power Manager can deliver 1.87 kW of demand reductions per device or 2.22 kW per household. Because Power Manager currently includes approximately 229,000 devices, the expected aggregate reduction capability is 427.1 MW.[1]

## Acknowledgements

The study required careful collaboration with the Duke Energy Carolina's evaluation and operations team, MadDash, Inc., Nexant field engineers, and Nexant's survey data collection lab. In specific, the inputs from Duke Energy's team—Bob Donaldson, Michael Corn, Marjan Salek, Rose Stoeckle, Danielle Maple and Regina Harris—were critical to proper implementation of the study and the analysis. Their comments and edits are reflected throughout the report. Marjan deserves special mention because she took on the critical task of addressing individual devices to the research group and, thus, enabled more extensive testing of operations. Dr. Michael Sullivan and Dr. Jon Cook provided critical input to the design of the study and the sample size simulations. A special thanks to Mad Dash, Inc. whose staff implemented the installation of air conditioner end use data loggers and inspected load control devices. Nexant field engineers were critical in retrieving end use data loggers and downloading the data. The Nexant survey data collection team led the recruitment of the end use sample, coordinated scheduling between field staff and customers, implemented the survey data collection, and coordinated the retrieval of data loggers.

[1] Aggregate impacts are presented throughout the report without rounding error. For example, while 1.87 kW x 229,000 devices equals 428.2 MW, the more granular impacts per device, 1.8652 kW per device were used to estimate aggregate impacts of 427.1 MW (1.8652 kW x 229,000 devices).

Table of Contents

## Table of Figures

## Table of Tables

# 1 Executive Summary

This report presents the results of Nexant's 2016 Power Manager impact and process evaluations for the Duke Energy Carolinas territory. Power Manager is a voluntary demand response program that provides incentives to residential customers who allow Duke Energy to reduce the use of their central air conditioners' outdoor compressors and fans on summer days with high energy usage. Events are typically called on the hottest summer days and are categorized into three groups: 50% cycling; 64% cycling; and 100% shed. During 50% and 64% cycling events, air conditioner control is randomly phased in over the first half hour of the event. At the end of those first 30 minutes, the cycling reduction is sustained through the remainder of the event (typically two or three hours). Over the last 30 minutes of a cycling event, air conditioning control is phased out in the order in which it began. During 100% shed events, which are designed for use during emergency conditions, all devices are instructed to instantaneously shed loads and deliver larger demand reductions than cycling events.

## 1.1 Impact Evaluation Key Findings

The impact evaluation results are based on customer regressions at the air conditioner (end use) and whole building levels. Nexant collected AC end use data via loggers installed directly on customers' outdoor air conditioner condensing units. Whole building loggers were installed at 122 premises, whereas end use loggers were installed on 144 air conditioners. In the end, 104 whole building loggers and 119 end use loggers were used in the final analysis dataset.[2] In situations where customers had more than one air conditioner, loggers were installed on each. The primary evaluation results are based on the end use data because it produces more precise estimates (due to the larger signal-to-noise ratio). Unless otherwise stated, load impacts are presented on a per customer basis throughout this report.

At the end of summer 2016, approximately 229,000 air conditioner units were actively participating in Power Manager and had load control devices installed. The average household had 1.19 load control devices installed.

Figure 1-1 summarizes the load impacts for all 2016 curtailment events as a function of temperature for whole building and end use logger data. A few notable trends are apparent. Perhaps most important, demand impacts grow in magnitude as temperatures increase—the Power Manager performs best when resources are needed most. Second, as expected, more extensive load control operations (e.g., 64% versus 50% cycling) lead to larger demand reductions. Under hotter conditions in 2016, load reductions exceeded 0.75 kW and 1.0 kW with 50% and 64% load cycling, respectively. Despite being called on cooler days, the 100% shed delivered load reductions of 1.46 kW per household on a 91.7˚F day and 1.82 kW per household on a 93.9˚F day. Third, the temperatures for the 100% shed event fell short of the 102˚F temperature peak expected in extreme years and, as a result, the 2016 shed events do not reflect the load shed capability used for planning.

[2] Some logging devices either did not record data, or returned spurious or unusable data.

Figure 1-1: Load Reduction by Cycling Level as a Function of Temperature

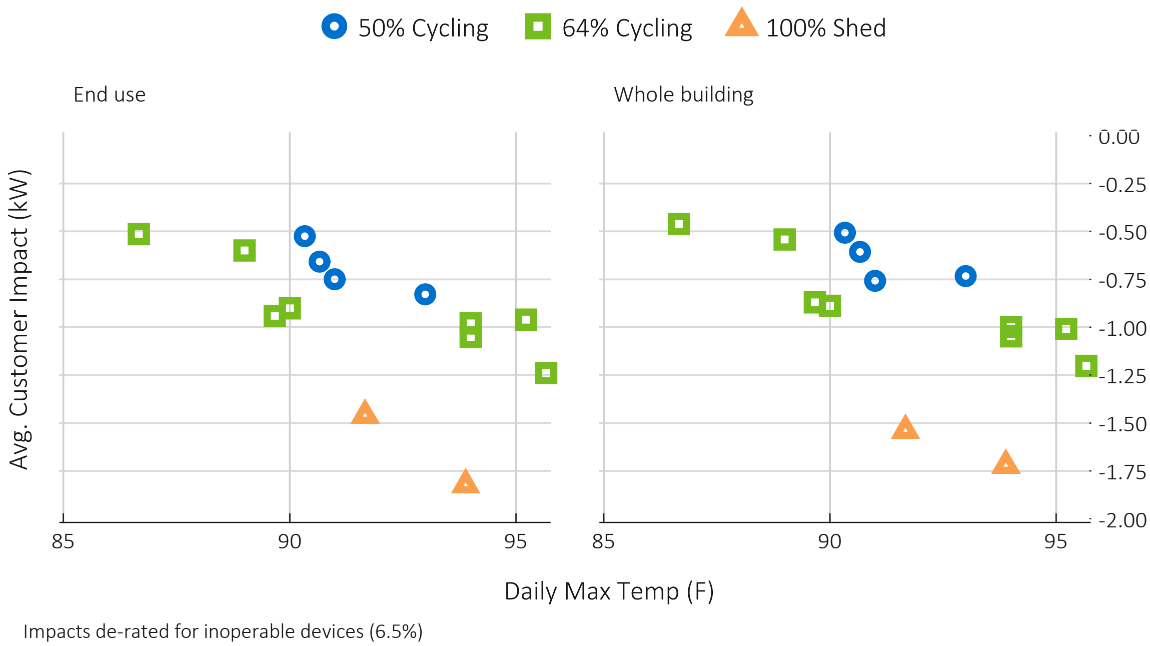



Table 1-1 summarizes the impacts attained during each event called in 2016 at the whole building and end use levels. By design, events were called under different weather conditions and for different dispatch windows to help define program performance under different operating conditions. At the end use level, average impacts were 0.69 kW, 0.90, and 1.64 kW during the 50%, 64%, and 100% control events, respectively, with larger impacts occurring on event days with higher temperatures. Average demand reductions were 0.65 kW, 0.88 kW, and 1.63 kW during the 50%, 64%, and 100% load shed events, respectively, at the whole house level. The demand impacts were nearly identical regardless of data source analyzed (i.e., whole building vs. end use) and differences are not statistically significant. There is no evidence that customers are compensating for air conditioner load control by increasing other loads.[3]

A key objective of the 2016 evaluation was to quantify the relationship between demand reductions, temperature, hour of day, and cycling strategy—referred to as the time-temperature matrix. In order to develop the time-temperature matrix, the 2016 events were intentionally called for a range of different temperatures, under different cycling strategies and for different dispatch data. The data collected on the weather sensitivity of air conditioner load and the reductions observed for events tested were used to develop estimates of demand reduction for a range of temperatures, including the 102˚F conditions that drive resource planning. The system temperature conditions are calculated by

[3] The comparison of air conditioner end use and whole building loads was implemented not just for Duke Energy Carolinas, but for Duke Energy Ohio, and Duke Energy Indiana. Each analysis produced similar findings. Similar tests have been conducted and PG&E, SDG&E, and IESO and reached similar conclusions.

averaging hourly temperatures of weather stations in Greenville/Spartanburg, South Carolina, Charlotte, North Carolina, and Greensboro, North Carolina. Because dispatch hours vary for individual events, throughout this document, the maximum system temperature for the day is reported for comparison.[4]

Table 1-1: Summary of Event Impacts for Whole Building and End Use

| True Cycle | Date | Event Start | Event End | Whole Building | | | End use (for household) | | | Daily Max ˚F |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Load without DR | Impact | % Impact | Load without DR | Impact | % Impact | |
| 50% | 7/20/2016 | 3:30 PM | 6:00 PM | 3.59 | -0.76 | -21.1% | 1.98 | -0.75 | -38.0% | 91.0 |
| | 9/6/2016 | 3:30 PM | 6:00 PM | 2.68 | -0.51 | -18.9% | 1.47 | -0.52 | -35.6% | 90.3 |
| | 9/8/2016 | 1:30 PM | 4:00 PM | 3.37 | -0.73 | -21.8% | 1.95 | -0.83 | -42.5% | 93.0 |
| | 9/14/2016 | 3:30 PM | 6:00 PM | 3.19 | -0.61 | -19.0% | 1.68 | -0.66 | -39.4% | 90.7 |
| | **Average** | **N/A** | **N/A** | **3.21** | **-0.65** | **-20.3%** | **1.77** | **-0.69** | **-39.1%** | **91.3** |
| 64% | 6/16/2016 | 2:30 PM | 5:00 PM | 3.30 | -1.00 | -30.3% | 1.91 | -0.98 | -51.4% | 94.0 |
| | 6/23/2016 | 2:30 PM | 6:00 PM | 3.46 | -1.05 | -30.2% | 2.03 | -1.05 | -51.7% | 94.0 |
| | 7/8/2016 | 2:30 PM | 6:00 PM | 3.94 | -1.01 | -25.7% | 2.28 | -0.96 | -42.1% | 95.2 |
| | 7/14/2016 | 1:30 PM | 4:00 PM | 3.85 | -1.20 | -31.2% | 2.30 | -1.24 | -53.9% | 95.7 |
| | 8/12/2016 | 3:30 PM | 6:00 PM | 3.36 | -0.87 | -25.9% | 1.96 | -0.94 | -48.0% | 89.7 |
| | 8/31/2016 | 3:30 PM | 6:00 PM | 3.39 | -0.89 | -26.2% | 1.90 | -0.90 | -47.5% | 90.0 |
| | 9/15/2016 | 3:30 PM | 6:00 PM | 2.62 | -0.54 | -20.7% | 1.40 | -0.60 | -42.9% | 89.0 |
| | 9/19/2016 | 1:30 PM | 4:00 PM | 2.64 | -0.46 | -17.5% | 1.33 | -0.51 | -38.6% | 86.7 |
| | **Average** | **N/A** | **N/A** | **3.32** | **-0.88** | **-26.4%** | **1.89** | **-0.90** | **-47.6%** | **91.8** |
| 100% | 8/26/2016 | 4:00 PM | 4:20 PM | 3.75 | -1.72 | -45.9% | 2.32 | -1.82 | -78.7% | 93.9 |
| | 9/7/2016 | 5:00 PM | 5:20 PM | 3.44 | -1.54 | -44.8% | 1.87 | -1.46 | -78.2% | 91.7 |
| | **Average** | **N/A** | **N/A** | **3.59** | **-1.63** | **-45.4%** | **2.09** | **-1.64** | **-78.5%** | **92.8** |

* Load impacts reported exclude the first half hour when air conditioner control is randomly phased in.

Because Power Manager delivers larger reductions when temperatures are hotter, the expected load reduction for a 102˚F day are 1.87 kW per device or 2.22 kW per household using 100% shed during the peak hour. At that temperature, expected reductions from non-emergency dispatch – defined as a three

[4] The temperatures during event hours may be lower since electric loads lag temperature peaks due to insulation in homes, coincidence of residential and nonresidential loads and occupancy patterns.

hour 64% cycling event, starting at 3pm – is 1.46 kW per device or 1.74 kW per customer. With 50% cycling, reductions are 0.89 kW per device or 1.05 kW per customer for a three hour event.

Key findings of the impact evaluation include:

- Demand reductions at the end use level were 0.69 kW for the average 50% cycling event, 0.90 for the average 64% cycling event, and 1.64 kW for the average 100% shed event.
- Demand reductions at the whole house level were 0.65 kW per household for the average 50% cycling event, 0.88 kW for the average 64% cycling event, and 1.63 kW for the average 100% shed event.
- Impacts grow larger in magnitude when temperatures are hotter and more AC loads are available for curtailment.
- There is a clear relationship between weather, degree of load cycling control, and the magnitude of impacts.
- Reductions exceeded 1.0 kW per participant multiple times with 64% cycling and 100% shed despite temperatures that fell far short of 102˚F used for system planning.
- Based on the empirical data, Power Manager is expected to deliver 1.87 kW per device or 2.22 kW per household if 100% shed becomes necessary on an extreme weather day, when temperatures are expected to reach 102 ˚F.
- There is no evidence that customers compensate for air conditioner curtailments by increasing other end uses—whole building impacts are indistinguishable from end use impacts.
- Based on field tests for 154 load control devices, 144 (93.5%) of devices were operable, with a 90% confidence interval of ±3.27%.

## 1.2 Process Evaluation Key Findings

The process evaluation was designed to inform efforts to continuously improve the program by identifying strengths and weaknesses, opportunities to improve program operations, adjustments likely to increase overall effectiveness, and sources of satisfaction or dissatisfaction among participating customers. The process evaluation consisted of telephone interviews with key program managers and implementers, a post-event survey implemented immediately after an event, and a nonevent day survey implemented on a day with event-like temperatures but without a load control event being called.

Key findings from the process evaluation include:

- 95 Power Manager participants were surveyed within 24 hours of the September 8 event, which had a high temperature of 94°F with a heat index of 95°F.
- 89 Power Manager participants were interviewed during a hot nonevent day, July 13, which had a high of 95°F with a heat index of 95°F. The nonevent day survey was used to establish a baseline for comfort, event awareness, and other key metrics.
- A strong majority of all respondents, 85%, reported that they are familiar with the Power Manager program.

- Only 12% of respondents on the event day reported that their homes were uncomfortable, while all of them experienced a load control event that afternoon. By comparison, 13% of Power Manager customers surveyed on a hot nonevent day reported they felt uncomfortably hot. This small difference is not statistically significant—we cannot conclude that there is a difference in customers' thermal discomfort due to Power Manager events.
- More than 85% of participants would recommend the Power Manager program to others.
- The Power Manager staff and vendors are customer focused and undertake a number of activities both during the load control season and afterward to ensure that participants are satisfied with their Power Manager program experience.

# 2 Introduction

This report presents the results of the 2016 Power Manager impact and process evaluations for the Duke Energy Carolinas (DEC) territory. Power Manager is a voluntary demand response program that provides incentives to residential customers who allow Duke Energy to reduce the use of their central air conditioner's outdoor compressor and fan during summer days with high energy usage. The DEC operations team schedules and calls Power Manager events for testing, economic, or system emergency purposes.

## 2.1 Key Research Questions

The study data collection and analysis activities were designed to investigate impact and process evaluation research questions.

### Impact Evaluation Research Questions

- What were the demand reductions achieved during each event called in 2016?
- Did impacts vary for customers in normal and high load control options?
- Were impacts at the whole building level (net) different from AC end use demand reductions (gross)?
- Do impacts vary based on the hours of dispatch and/or weather conditions? If so, how?
- What is the device failure rate?

### Process Evaluation Research Questions

- What is the extent to which participants are aware of events, bill credits, and other key program features?
- What is the participant experience during events?
- What are the motivations and potential barriers for participation?
- What are the processes associated with operations and program delivery?
- What are program strengths and areas for potential improvement?

## 2.2 Program Description

Power Manager is a voluntary demand response program that provides incentives to residential customers who allow Duke Energy to cycle their central air conditioner's outdoor compressor and fan on summer days with high energy usage. All Power Manager participants have a load cycling switch device installed on all of their outdoor air conditioner units. The device reduces the customer's air conditioner run time when a Power Manager event is called. Duke Energy Carolinas (DEC) initiates events by sending a signal to all participating devices through its own paging network. The signal instructs the switch devices to cycle or fully shed the air conditioning system, reducing AC load during events. The DEC operations team schedules and calls Power Manager events for testing, economic, or system emergency purposes.

The DEC Power Manager event season runs between June and September and participants receive financial incentives for their participation in the form of $8 credits applied to each of their July through October bills. DEC switches use a TrueCycle algorithm, which uses stored historic data, to estimate the run time (or duty cycle) of air conditioners as a function of hour of day and temperature at each specific site, and aims to curtail use by a specified amount—50%, 64%, or 100% (emergency shed).

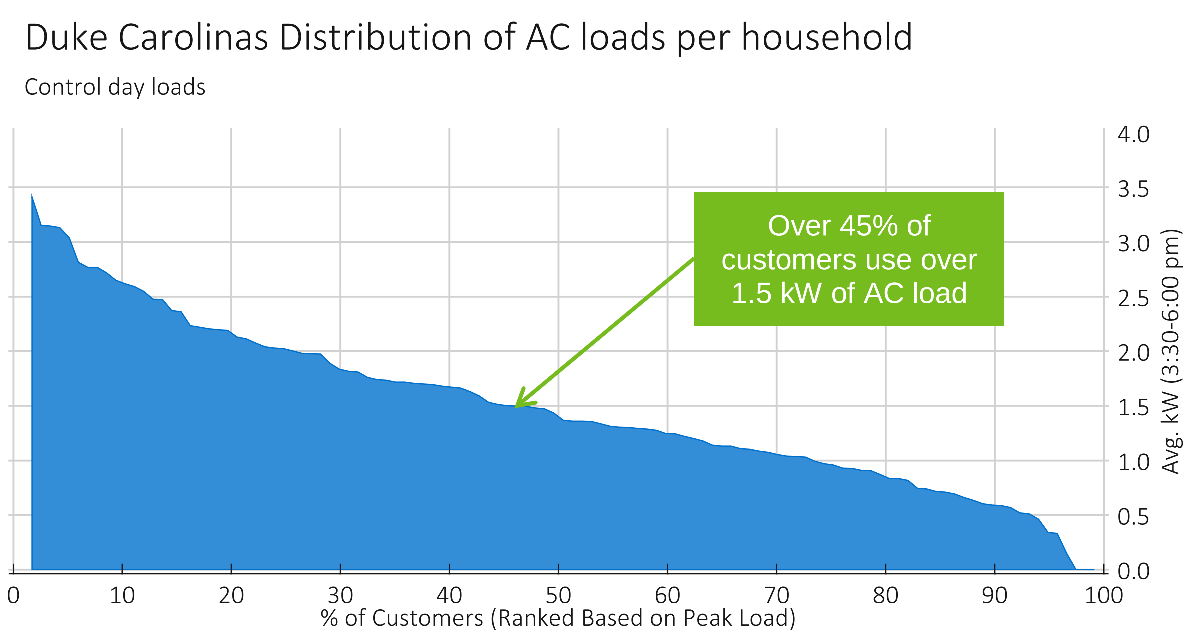
## 2.3 Participant Characteristics

The Duke Energy Carolinas service territory spans much of the western half of North Carolina and northwestern South Carolina. By the end of September 2016, slightly more than 192,000 customers and 229,000 air conditioners were participating in Power Manager. On average, there are 1.19 air conditioner units per customer. Duke Energy Carolinas serves approximately 2.15 million residential customers, of which roughly 1.27 million are eligible for the Power Manager program. Overall, Duke Energy Carolinas has enrolled 15.1% of eligible customers to date.

A sample of 122 Power Manager participants were selected for inclusion in Nexant's impact evaluation, comprising a total of 144 end use (AC) loggers. Nexant compiled end use data from the 144 loggers and assessed it for quality and completeness. Of the 144 devices installed, 119 loggers returned usable end use data, making up the final impact analysis dataset.

Nexant isolated customers' AC system loads during peak hours (3:30 to 6:00pm) on nonevent days with high average temperatures in order to examine typical AC loads on hot summer days. These are generally analogous to event days and provide a reasonable estimate of what customer AC loads would have been in the absence of a curtailment event. Figure 2-1 shows the distribution of average customer loads (kW) during peak hours on nonevent days. Roughly 45% of sampled customers use more than 1.5 kW of AC load under these typical event conditions.

Figure 2-1: Distribution of Air Conditioner Peak Period Loads

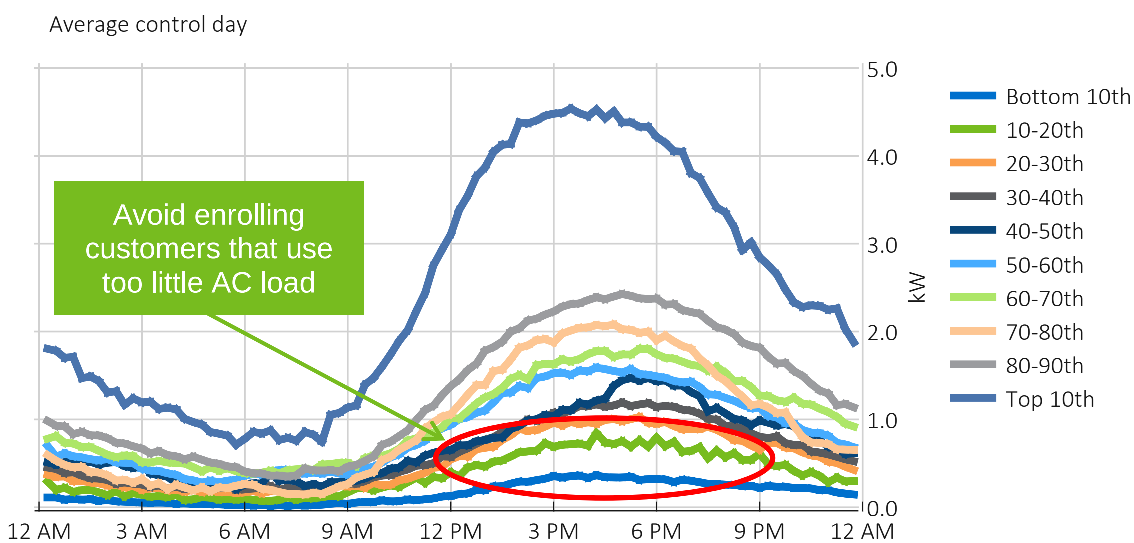


One of the advantages of end use data collection is the ability to assess whether customers use their air conditioners during key hours on hotter days. By design, events were not called on all of the hottest summer days, enabling Nexant to assess typical air conditioner use absent load curtailment events. A total of 47 nonevent days were identified having daily maximum temperatures exceeding 86°F and an average daily maximum temperature of 90°F, compared to an average maximum temperature of 92°F for actual event days.

Figure 2-1 shows the distribution of average air conditioner unit demand during peak hours across sampled customers on nonevent days. Nexant isolated the hours 4 to 6pm to generate the distribution as this period aligns with the timing for most Power Manager events. Power Manager participants' air conditioner use varies substantially, reflecting different occupancy schedules, comfort preferences, and thermostat settings. Roughly 45% of air conditioner loads exceed 1.5 kW during peak hours. As with any program, consumption varies by customer for a variety of reasons. A portion of enrolled customers use little or no air conditioning during late afternoon hours on hotter days. These customers are, in essence, free riders since they receive the participation incentive without providing AC load for curtailment. However, the bulk of the costs for recruitment, equipment, and installation have already been sunk for these customers and, as a result, removing them from the program may not substantially improve cost effectiveness.

Nexant then categorized customers into deciles by average daily loads on nonevent days. This process allows for more targeted consideration of customers that typically use either extremely high or extremely low loads during event-like conditions. Figure 2-2 shows average AC load shapes by decile for sampled participants on nonevent days that are comparable to event days. Despite the general size of AC loads, some customers have small AC loads during peak hours. In general, customers that make up these lower deciles are not ideal candidates for program participation due to relatively low potential for load shed impacts.

Figure 2-2: Air Conditioner End Use Hourly Loads by Size Decile



## 2.4 2016 Event Characteristics

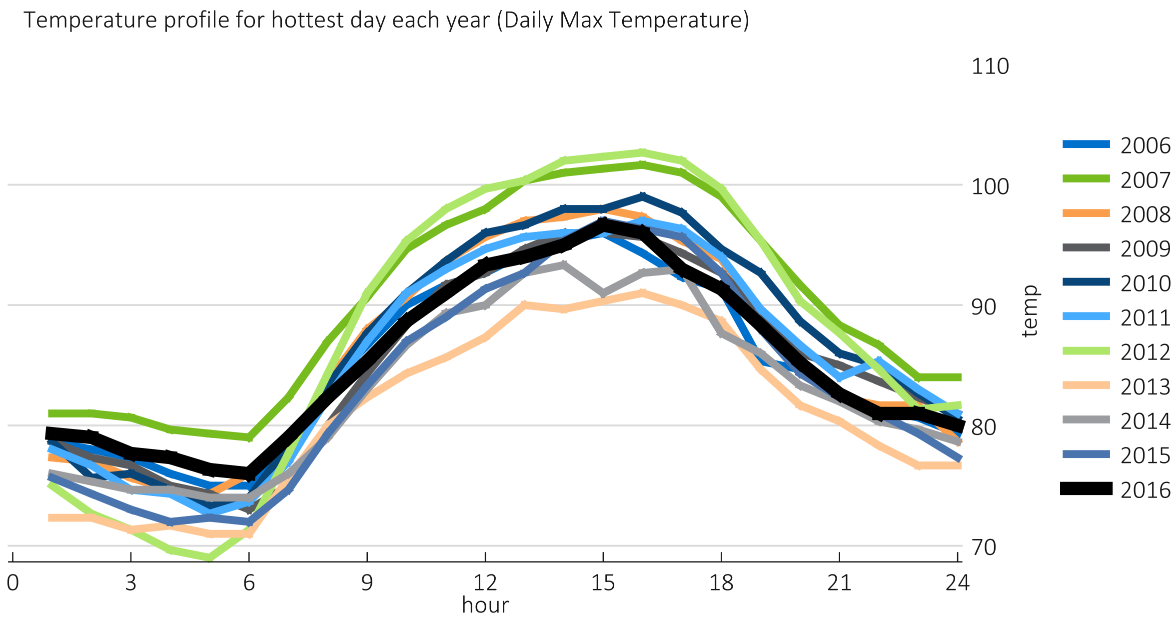
In 2016, Duke Energy Carolinas dispatched Power Manager events 14 times. Some of these events involved dispatching all of the customers enrolled in the program, while other events were only called for customers in the research group in order to provide data for this analysis. By design, events included a wide range of dispatch hours, weather conditions, and control levels. Both test events of the 100% emergency shed lasted 20 minutes; and, all systems were affected simultaneously at the outset of the event window. All of the 50% and 64% cycling events were called at 1:30 pm, 2:30 pm, or 3:30 pm and lasted either 2.5 hours or 3.5 hours. Control of affected air conditioning units was phased in at random over the first 30 minutes of each event. Likewise, the last 30 minutes of these events allowed air conditioning units to resume normal operations in the order they were first controlled. The demand reductions reported in this report for 50% and 64% cycling events exclude the random phase-in and phase-out periods of each event because those periods do not reflect demand reductions when all units are being cycled. Table 2-1 lists the events that were called during the summer of 2016.

Table 2-1: 2016 Event Operations and Characteristics

| TrueCycle Level | Event Date | Start Time | End Time | Temperature | # of Customers |
|---|---|---|---|---|---|
| 50% | 7/20/2016 | 3:30 PM | 6:00 PM | 91.0 | ~120 |
| | 9/6/2016 | 1:30 PM | 4:00 PM | 90.3 | ~120 |
| | 9/8/2016 | 3:30 PM | 6:00 PM | 93.0 | 189,605 |
| | 9/14/2016 | 3:30 PM | 6:00 PM | 90.7 | ~120 |
| 64% | 6/16/2016 | 1:30 PM | 4:00 PM | 94.0 | ~120 |
| | 6/23/2016 | 2:30 PM | 5:00 PM | 94.0 | 185,928 |
| | 7/8/2016 | 3:30 PM | 6:00 PM | 95.2 | ~120 |
| | 7/14/2016 | 2:30 PM | 6:00 PM | 95.7 | 186,744 |
| | 8/12/2016 | 3:30 PM | 6:00 PM | 89.7 | ~120 |
| | 8/31/2016 | 3:30 PM | 6:00 PM | 90.0 | ~120 |
| | 9/15/2016 | 1:30 PM | 4:00 PM | 89.0 | ~120 |
| | 9/19/2016 | 2:30 PM | 6:00 PM | 86.7 | 190,564 |
| 100% | 8/26/2016 | 4:00 PM | 4:20 PM | 93.9 | ~120 |
| | 9/7/2016 | 5:00 PM | 5:20 PM | 91.7 | ~120 |

In comparison to the immediately prior 10 years, 2016 was neither extremely hot nor cool for DEC territory. Figure 2-3 shows how the maximum temperature in 2016 compares to historical hourly temperatures for the weekday with the highest daily maximum temperature. The peak day temperatures, however, fell short of the 102°F used for planning.

Figure 2-3: Comparison of 2016 Maximum Temperature to Historical Years (2006-2016)



# 3 Methodology and Data Sources

This section details the study design, data sources, sample sizes, and analysis protocols for both the impact and process evaluations. For clarity, details about the methodologies for the impact and process evaluations are presented separately.

## 3.1 Impact Evaluation Methodology

The 2016 Power Manager impact evaluation included three main activities designed to meet the research objectives. The primary evaluation results are based on a combination of end use (AC) and whole building data. Table 3-1 summarizes the components of the impact evaluation.

Table 3-1: Summary of Impact Evaluation Components

| Evaluation Component | Description |
|---|---|
| Air conditioner end use meter sample (gross) | ▪ Data loggers installed on 144 devices, 119 devices used for analysis[5]<br>▪ Spot measurements of voltage, amps, kW, and connected load conducted at 122 sites<br>▪ Used to compare end use to whole building demand reductions and assess if customers compensated for air conditioner curtailments<br>▪ Used nonevent days to infer the baseline<br>▪ Regression model selected based on out of sample testing of multiple models |
| Whole building data for customers with end use metered air conditioners (net) | ▪ Whole house interval meters installed for same households with air conditioner end use data loggers<br>▪ Used to compare end use (gross) to whole building demand reductions (net) and assess if customers compensated for air conditioner curtailments<br>▪ Used nonevent days to infer the baseline<br>▪ Regression model selected based on out of sample testing of multiple models |
| Device operability inspections and analysis | ▪ Field inspection of 154 devices, of which 10 (6.5%) were inoperable<br>▪ Event day shape analysis for all customers to identify devices that are and are not curtailing loads during events |

## 3.2 Analysis Protocol for End Use Metered Customers

The DEC study included end use metering for a sample of 144 air conditioner units at 122 households. The main purpose was to assess if whole house demand reductions matched end use demand reductions, or if customers were compensating for air conditioner curtailments by increasing use of fans or other equipment. The field study also provided the opportunity to inspect devices. Nexant was responsible

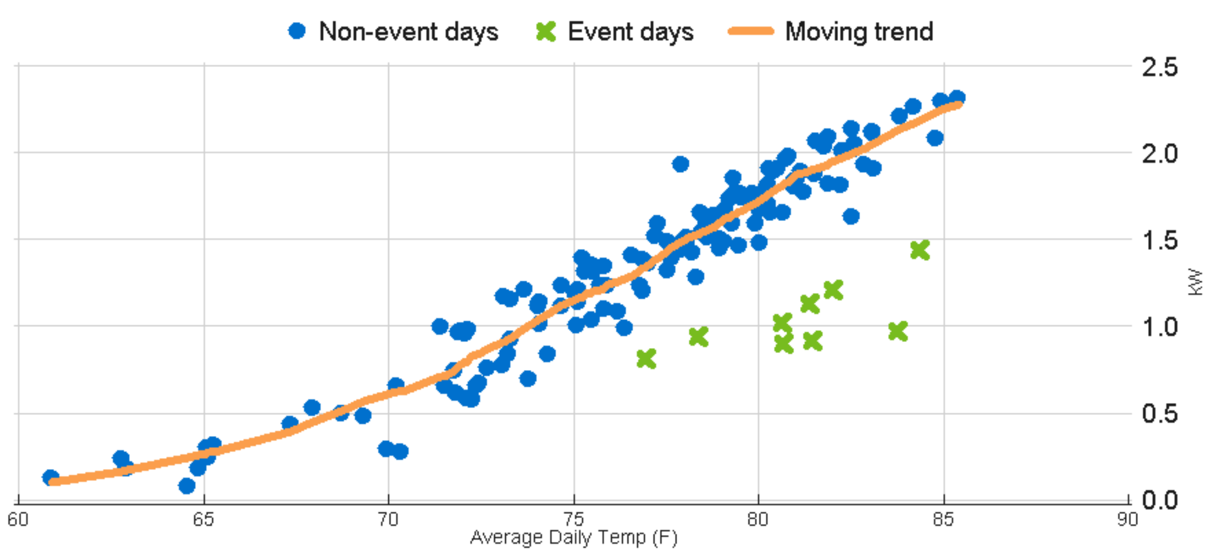
[5] Some device loggers either did not record data for the full summer or did not download data.

for all aspects of the field work, including customer recruitment, scheduling, device inspection, spot measurements, data logger installation, data logger retrieval, data download, and data analysis. For sites with end use metering, demand reductions were calculated using the same method to allow direct comparison between whole building and end use demand reductions.

Nexant modeled the relationship between weather and demand on hot nonevent days to establish what customer energy use patterns would have been absent curtailments, known as the counterfactual. This approach works because the intervention—air conditioner curtailments—is introduced on some days and not on others, making it possible to observe load patterns with and without demand reductions. The repeated ON/OFF pattern enables Nexant to assess whether the outcome—electricity use—rises or falls with the presence or absence of event dispatch instructions. This approach hinges on having comparable nonevent days. When all of the hottest days are event days, the counterfactual is based on extrapolating trends beyond the range of nonevent temperatures, producing less accurate and less unreliable impact estimates for the hottest days. By design, DEC avoided dispatching Power Manager resources on all of the hottest days.

Figure 3-1 illustrates the underlying concept using actual DEC end use load data. The blue circles reflect the individual nonevent weekdays and the orange line shows the trend between peak hour loads and weather. The green X's show the load during event days. The regression modeling calculates the demand reduction as the difference between the estimated loads absent air conditioners and actual loads during event days. Figure 3-1 is simplified for illustration purposes. In practice, regression modeling typically includes explanatory variables other than weather, such as day of week effects and seasonal or monthly effects.

Figure 3-1: Peak Hour Loads (4 to 6pm) as a Function of Temperature



## 3.3 Data Sources

For the impact evaluation, interval data was collected both at the end use and whole building levels to allow for net impacts vs. gross impacts analysis. End use data was collected using data loggers that were installed on individual AC units. Whole building data was recorded by revenue grade interval meters installed by Duke Energy.

End use and whole building data was used for the same group of customers to eliminate the potential for sampling variability from the net vs. gross analysis. The sample used for the impact evaluation was a simple random sample drawn from the DEC Power Manager program population. Table 3-2 summarizes the whole building and end use data collection activities completed for Nexant's impact analysis.

Table 3-2: Data Collected for Evaluation

| Data Collection | Installed or Available | Used for Analysis |
|---|---|---|
| Whole building data | 122 | 104 |
| AC end use data | 144 | 119 |
| Spot measurements | 139 | 119 |
| Devices | 144 | 119 |
| Device inspections | 154 | 154 |

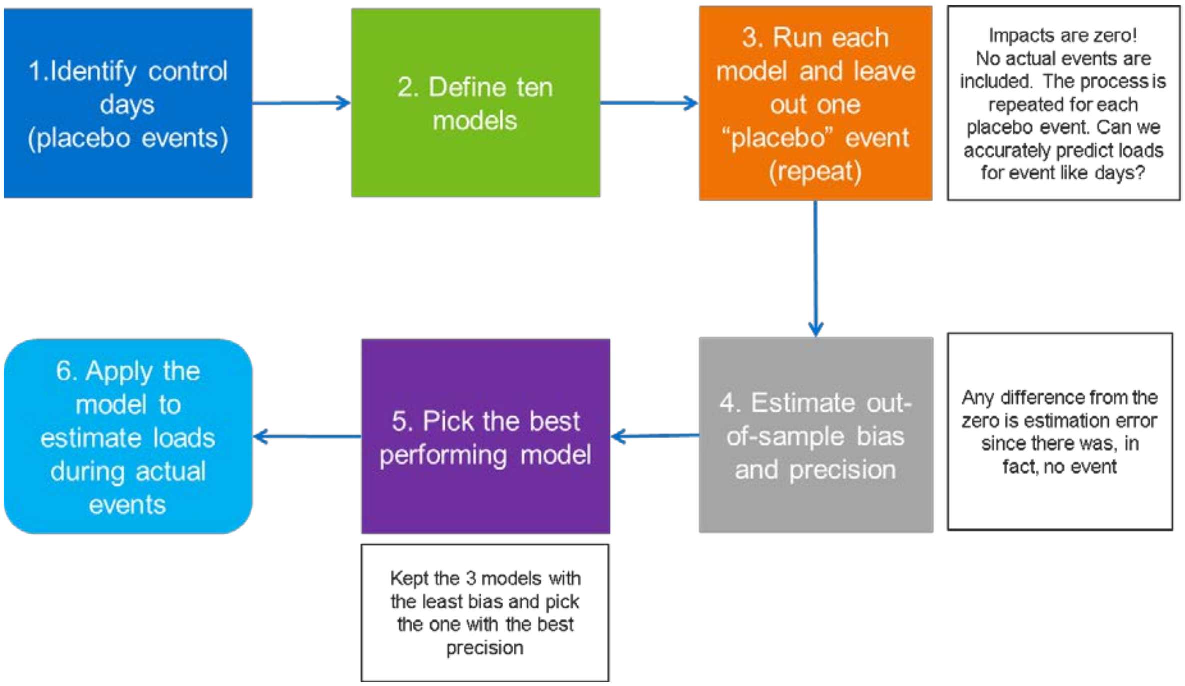
Nexant also requested data related to enrollment, demographics, weather, event details, and past impacts.

## 3.4 Model Selection Process

A key question every evaluator must address is how to select a model that produces the most accurate and precise counterfactual. In many instances, multiple counterfactuals are plausible but provide different estimated demand reductions. The model selection was based on testing 10 distinct model specifications and employing a systematic approach to identify the most accurate and precise estimation model, described in Figure 3-2.

The process relies on placebo tests. First, the model specifications are defined. Second, hotter, nonevent days are defined as placebo days. Because load control devices were not activated during these days, the impacts are by definition zero and any estimated impact by the models is in fact due to model error. Third, each model is run using nonevent data, leaving out a single placebo day. The regression model is used to predict electricity use on the placebo event day that was withheld, i.e., an out-of-sample prediction. Nexant repeated the process for each placebo day and recorded the actual and predicted loads for each placebo event day. A total of 47 placebo days were employed. Fourth, the out-of-sample predictions for each model are compared to actual electricity usage observed on that day, which are used to calculate metrics for bias and precision. The best model was identified by selecting the model with the highest precision from among the three models with the least bias. This best performing model is used to estimate the counterfactual for actual event days.

Figure 3-2: Model Selection




## 3.5 Bias and Precision Metrics

Table 3-3 summarizes metrics for bias and precision.[6] Bias metrics measure the tendency of different approaches to over or under predict and are measured over multiple days. The mean percent error (MPE) describes the relative magnitude and direction of the bias. A negative value indicates a tendency to under predict and a positive value indicates a tendency to over predict. This tendency is best measured using multiple days. The precision metrics describe the magnitude of errors for individual event days and are always positive. The closer they are to zero, the more precise the results. The absolute value of the mean percentage error is used to narrow the models to the three candidates with the least bias. The coefficient of variation of the root mean square error, or CV(RMSE), metric is used to identify the most precise model from among the three candidates with smallest bias.

[6] Bias is also referred to as accuracy. Precision is sometimes called goodness-of-fit.

Table 3-3: Measures of Bias and Precision

| Type of Metric | Metric | Description | Mathematical Expression |
|---|---|---|---|
| Bias | Average Error | Absolute error, on average | $AE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)$ |
| | Mean Percentage Error (MPE) | Indicates the percentage by which the measurement, on average, over or underestimates the true demand reduction. | $MPE = \frac{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)}{\bar{y}}$ |
| Precision | Root mean squared error | Measures how close the results are to the actual answer in absolute terms, penalizes large errors more heavily | $\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$ |
| | CV(RMSE) | Measures the relative magnitude of errors across event days, regardless of positive or negative direction (typical error) | $CV(RMSE) = \frac{RMSE}{\bar{y}}$ |

Table 3-4: Model Selection

| Model | Variables | End-Use | | | | Whole building | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Bias | | Precision | | Bias | | Precision | |
| | | Avg. Error | Mean Percent Error | Root mean square error | Normalized RMSE | Avg. Error | Mean Percent Error | Root mean square error | Normalized RMSE |
| 1 | - Pre-event load (11 am to 1 pm)<br>- Cooling degree hours (Base 70F)<br>- Day of week and month | -0.01 | -0.7% | 0.11 | 7.8% | -0.03 | -0.9% | 0.17 | 5.9% |
| 2 | - Pre-event load (11 am to 1 pm)<br>- Cooling degree days (Base 65F)<br>- Day of week and month | -0.02 | -1.2% | 0.14 | 9.6% | -0.03 | -1.1% | 0.19 | 6.6% |
| 3 | - Pre-event load (11 am to 1 pm)<br>- Maximum temperature for day<br>- Day of week and month | 0.00 | 0.1% | 0.16 | 10.7% | 0.00 | -0.1% | 0.21 | 7.2% |
| 4 | - Pre-event load (11 am to 1 pm)<br>- Avg. temperate in prior 24 hours<br>- Day of week and month | -0.02 | -1.5% | 0.18 | 12.1% | -0.04 | -1.3% | 0.23 | 8.0% |
| 5 | - Pre-event load (11 am to 1 pm)<br>- CDH and CDD<br>- Day of week and month | -0.01 | -0.7% | 0.11 | 7.9% | -0.03 | -0.9% | 0.17 | 5.9% |
| 6 | - Pre-event load (11 am to 1 pm)<br>- Avg. temperate in prior 24 hours and current CDH<br>- Day of week and month | -0.01 | -0.7% | 0.11 | 7.9% | -0.03 | -0.9% | 0.17 | 6.0% |
| 7 | - Pre-event load (11 am to 1 pm)<br>- Average CDH in prior 6 hours and current CDH<br>- Day of week and month | -0.01 | -0.4% | 0.11 | 7.3% | -0.01 | -0.4% | 0.16 | 5.5% |
| 8 | - Pre-event load (11 am to 1 pm)<br>- Average CDH in prior 12 hours and current CDH<br>- Day of week and month | -0.01 | -0.4% | 0.11 | 7.6% | -0.02 | -0.6% | 0.16 | 5.7% |
| 9 | - Pre-event load (11 am to 1 pm)<br>- Average CDH in prior 18 hours and current CDH<br>- Day of week and month | -0.01 | -0.7% | 0.11 | 7.8% | -0.02 | -0.9% | 0.17 | 5.9% |
| 10 | - Pre-event load (11 am to 1 pm)<br>- Average CDH in prior 24 hours and current CDH<br>- Day of week and month | -0.01 | -0.7% | 0.11 | 7.9% | -0.03 | -0.9% | 0.17 | 6.0% |

## 3.6 Device Operability Testing Protocols

Nexant installed end use data loggers only on air conditioning units having functioning DLC switches at the time of the installation. Switches were inspected to ensure that devices were properly connected and had successfully received a test signal. At the beginning of the site visits for logger installations, field technicians conducted a visual inspection of the installed switch device to determine that it was properly connected and verified that the green light indicating proper connectivity was illuminated. Inspections were conducted in the following areas:

- Load control device
  - Presence
  - Proper installation
  - Physical condition
  - Operability
- Device connection wires
  - Presence
  - Physical condition
  - Secure connection

Systems with switches that failed inspections in any of these areas were abandoned and no loggers were deployed. This data allows for estimates of the number of switch failures that result from several different causes. Switch operability data was used to adjust the per customer impacts generated from the sample consisting of functioning switches when estimating aggregate impacts for the Power Manager population. Results of the switch device inspections are presented in Section 6.1.

## 3.7 Process Evaluation Methodology

Table 3-5: Summary of Evaluation Activities

| Data Collection Technique | Description of Analysis Activities Using Collected Data | Sample Size | Precision / Confidence Level |
|---|---|---|---|
| Interviews of key contacts | Interviews with Duke Energy staff will document program processes, identify strengths/weaknesses and provide a foundation for understanding the customer experience. | 2-4 | NA |
| Post-event survey | Phone survey of Power Manager customers immediately after an event to assess event awareness, program strengths/weaknesses customer experience during events and motivations for participation. | 68 | 90/10 |
| Nonevent survey | Similar to post-event survey, but conducted after a hot, nonevent day. Comparing nonevent and post-event survey responses will identify customer awareness of events and effects of events on customer comfort. | 68 | 90/10 |

The process evaluation included four primary data collection tasks in order to achieve the research objectives listed in Table 3-5.

**Review program documentation and analyze program database**—Process evaluation should be guided by a thorough understanding of the primary activities of any program, the marketing messages used to recruit and support participants, and any formal protocols that guide processes. For demand response programs, it is particularly important to understand the event notification procedures, any opt-out processes that exist, and how bill credits are communicated and applied. It is also important to understand how the program opportunity is communicated and the types of encouragement provided to participating households. These communications are often the source of program expectations, which can affect participant satisfaction. To support this task, Nexant requested copies of internal program manuals and guidelines as well as copies of marketing materials. The program database analysis consisted of an examination of the distribution of bill credits and incentive payments, the program tenure, load curtailed per household, and other variables that inform indications of program progress.

**In-depth interviews with key program stakeholders**—Program stakeholders include program staff, implementation contractors, and staff elsewhere in the utility with insight into program plans and operations, emerging issues, and the expected customer experience. The interviews conducted for the 2016 evaluation informed the customer survey design and confirmed the evaluation team's understanding of key program components. Because Power Manager is implemented consistently across jurisdictions, a common interview structure was feasible.

Goals of the interviews included:

- Understanding marketing and recruitment efforts, including lessons learned about the key drivers of enrollment;
- Identifying "typical" Power Manager households, including characteristics of households that successfully participate for multiple years;
- Describing event processes;
- Understanding opt-out procedures;
- Confirming enrollment incentive levels and how event incentives are explained to customers;
- Understanding any differences in customer experience that might occur depending upon whether or not an event is called for economic or emergency purposes;
- Identifying any numeric or other program performance goals (kW enrollment, number of households, notification timelines) established for Power Manager; and
- Describing the working relationship between Duke Energy and the program implementer including the allocation of program responsibilities.

**Post-event surveys**—Guided by information obtained from stakeholder interviews and a review of program guidance documents (including any notification protocols), Nexant developed a survey for participating customers that was deployed immediately following a demand response event. The survey was designed to be deployed via phone and email to maximize response rate in the 24 to 48 hour window following an event. The post-event survey addressed the following topics:

- Awareness of the specific event day;
- Experience of and satisfaction with the event notification process;

- Actions taken in advance of the event to mitigate the effect of AC cycling;
- Any actions taken during the event to increase household comfort. Do participants report changing AC settings, using other equipment (including window units, portable units, or ceiling fans) to mitigate heat buildup? Were participants home during the event? Are they usually home during that time period?
- Satisfaction with the Power Manager program, the event bill credits earned, and the number of events typically called;
- Expectations and motivations for enrolling. What did participants expect to gain from enrollment? To what extent are they motivated to earn incentive payments versus altruistic motivations such as helping to address electricity shortfalls during periods of high peak demand and/or reducing the environmental effects of energy production?
- Retention and referral. For how many years have participants been enrolled? Do participants expect to remain enrolled in the program in future years? Would they recommend the program to others? Are there people they would discourage from enrolling? What types of people, and why?

To ensure that the survey accurately assessed the experiences of customers during a curtailment event, questions were finalized and fully programmed by May 1 to enable deployment within 24 hours after an event. Working with Duke Energy and the impact evaluation team, Nexant prepared a random sample of participant households prior to event notification to receive the post-event survey. This sample was linked to the survey software and ready to deploy as soon as the event ended. Any participants for whom email addresses were available received an email invitation with a link to the survey URL. Up to half of the expected sample (35 households) were surveyed by phone to ensure completes by both modes and improve representativeness.

Nonevent program surveys—In addition to the post-event survey, the evaluation team prepared a survey to be deployed immediately following a hot, nonevent day. This nonevent day survey was nearly identical to the post-event survey to facilitate comparison with the results of the event day survey, with only references to specific event awareness removed. Like the post-event survey, the nonevent survey was developed, approved, and programmed prior to the demand response season to enable immediate deployment on a sufficiently comparable nonevent day. The nonevent survey sample was developed prior to the demand response season and linked to the programmed survey. Similar to the post-event survey, a survey link was sent via email to participants with email addresses. This improved the speed of data collection and the representativeness of the sample.

# 4 2016 Event Results

The Power Manager program in the DEC territory was evaluated using within-subjects regression of load data collected from a sample of program participants. The analysis used end use data collected from a random sample of Power Manager customers' outdoor air conditioning units, as well as whole house data from the same group of customers. The same regression model was applied to both sets of data to ensure consistency in the analysis and to allow for valid comparison between results.

One of the primary objectives of the study was to understand the load impacts attributable to Power Manager under a variety of conditions. By design, events were called on days with varying temperature conditions. The analysis of both end use and whole house level data allowed for a comparison of the two in order to determine whether whole house impacts would predict similar impacts to those from end use data. Smaller whole house demand reductions would imply that customers offset air conditioning curtailments through other cooling end uses (e.g., fans). Among its findings, Nexant's impact evaluation determined that there is no evidence that customers compensate for air conditioner curtailments by increasing other end uses—whole building impacts are virtually indistinguishable from end use impacts.

The primary results from the evaluation are based on the end use demand reduction. The estimates for end use data are more precise due to a larger signal-to-noise ratio. The percent reduction is larger and the remaining noise after modeling is smaller.

## 4.1 End Use Results

The event day load impacts at the end use level are presented in Table 4-1. At the end use level, load reductions are estimated to be 39.1%, 47.6%, and 78.5% of the base load at the 50%, 64%, and 100% control levels, respectively. In absolute terms, kW impacts are estimated to be 0.69 kW, 0.90 kW, and 1.64 kW at 50%, 64%, and 100% control, respectively, for the average event.

The four 50% true cycling events achieved an average load reduction of 0.69 kW, or 39.1% of the 1.77 kW base load. The model found a 90% confidence band ranging from 0.56 kW to 0.82 kW. Among the eight 64% cycling events, the average impact was 0.90 kW, or 47.6% of the 1.89 kW base load. End use impacts approximated or exceeded 1.0 kW during multiple events. The two emergency 100% shed events achieved the largest impacts, despite relatively cool temperatures. The average impact for these events was 1.64 kW, or roughly 78.5% of the 2.09 kW average base load. The average impact for these events had a 90% confidence band ranging from 1.50 kW to 1.78 kW. Impacts shown in Table 4-1 represent the average load reduction during the duration of each event.

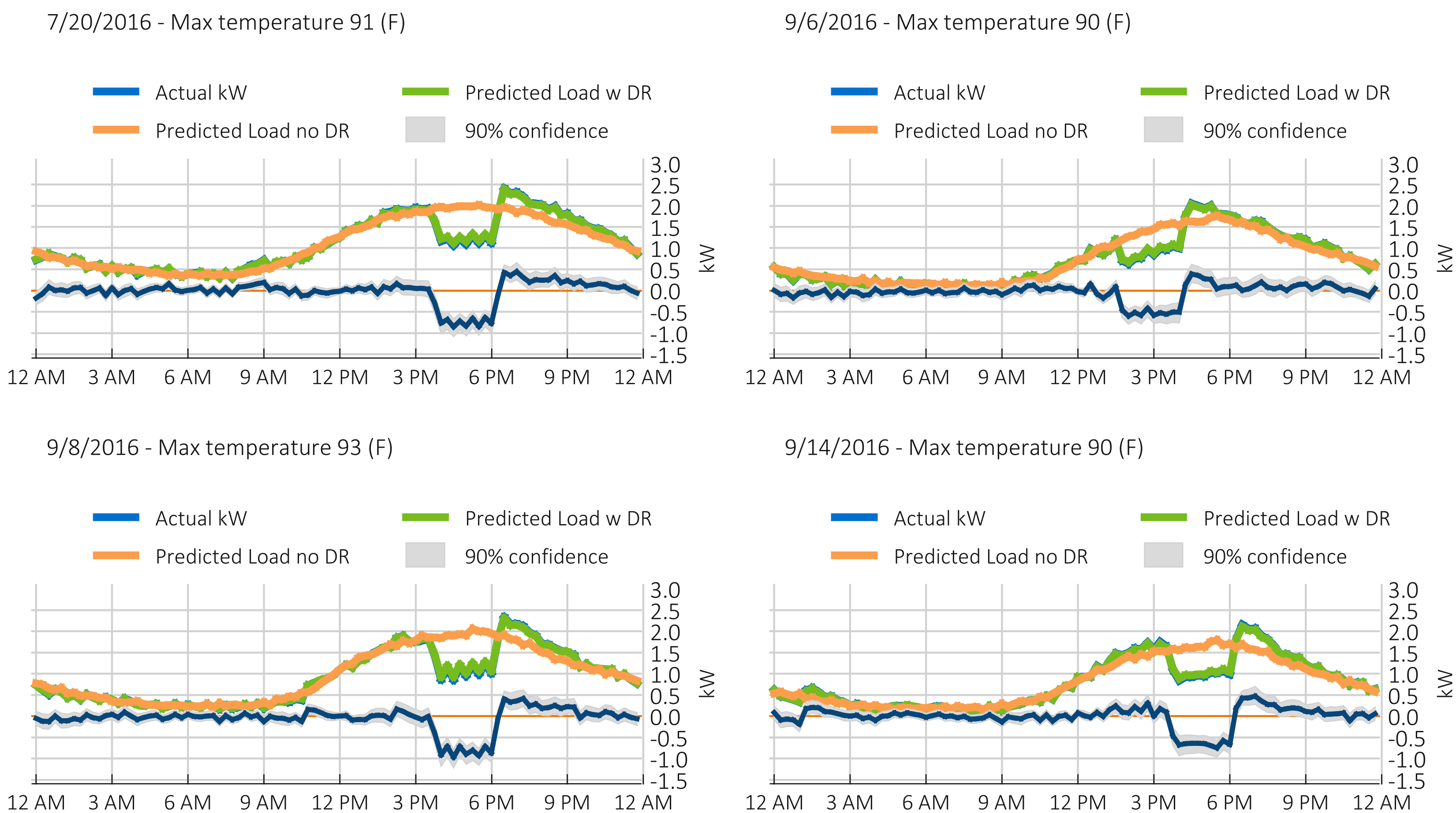
Despite being called on cooler days, the 100% shed delivered load reductions of 1.46 kW per household on a 91.7˚F day and 1.82 kW per household on a 93.9˚F day. Because the temperatures for the 100% shed event fell short of the 102˚F conditions expected in extreme years, the 2016 shed events do not reflect the load shed capability used for planning. The process for estimating the demand reduction capability available for 102˚F conditions are described in Section 6.

Table 4-1: End Use Event Day Load Impacts

| True Cycle | Date | Load without DR | Impact | Std. error | 90% Confidence Interval | | % Impact | 90% Confidence interval | | Daily Max (F) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower bound | Upper bound | | Lower Bound | Upper Bound | |
| 50% | 7/20/2016 | 1.98 | -0.75 | 0.13 | -0.54 | -0.96 | -38.0% | -27.5% | -48.4% | 91.0 |
| | 9/6/2016 | 1.47 | -0.52 | 0.13 | -0.32 | -0.73 | -35.6% | -21.5% | -49.7% | 90.3 |
| | 9/8/2016 | 1.95 | -0.83 | 0.13 | -0.61 | -1.05 | -42.5% | -31.2% | -53.7% | 93.0 |
| | 9/14/2016 | 1.68 | -0.66 | 0.13 | -0.44 | -0.87 | -39.4% | -26.5% | -52.2% | 90.7 |
| | **Average** | **1.77** | **-0.69** | **0.08** | **-0.56** | **-0.82** | **-39.1%** | **-31.7%** | **-46.4%** | **91.3** |
| 64% | 6/16/2016 | 1.91 | -0.98 | 0.12 | -0.78 | -1.18 | -51.4% | -41.0% | -61.8% | 94.0 |
| | 6/23/2016 | 2.03 | -1.05 | 0.13 | -0.84 | -1.27 | -51.7% | -41.2% | -62.3% | 94.0 |
| | 7/8/2016 | 2.28 | -0.96 | 0.13 | -0.75 | -1.17 | -42.1% | -32.8% | -51.4% | 95.2 |
| | 7/14/2016 | 2.30 | -1.24 | 0.13 | -1.03 | -1.45 | -53.9% | -44.8% | -62.9% | 95.7 |
| | 8/12/2016 | 1.96 | -0.94 | 0.13 | -0.73 | -1.15 | -48.0% | -37.3% | -58.8% | 89.7 |
| | 8/31/2016 | 1.90 | -0.90 | 0.13 | -0.70 | -1.11 | -47.5% | -36.6% | -58.3% | 90.0 |
| | 9/15/2016 | 1.40 | -0.60 | 0.12 | -0.40 | -0.80 | -42.9% | -28.5% | -57.3% | 89.0 |
| | 9/19/2016 | 1.33 | -0.51 | 0.13 | -0.30 | -0.73 | -38.6% | -22.6% | -54.5% | 86.7 |
| | **Average** | **1.89** | **-0.90** | **0.08** | **-0.77** | **-1.02** | **-47.6%** | **-40.9%** | **-54.2%** | **91.8** |
| 100% | 8/26/2016 | 2.32 | -1.82 | 0.14 | -1.60 | -2.05 | -78.7% | -69.0% | -88.4% | 93.9 |
| | 9/7/2016 | 1.87 | -1.46 | 0.14 | -1.24 | -1.68 | -78.2% | -66.3% | -90.2% | 91.7 |
| | **Average** | **2.09** | **-1.64** | **0.08** | **-1.50** | **-1.78** | **-78.5%** | **-71.9%** | **-85.1%** | **92.8** |

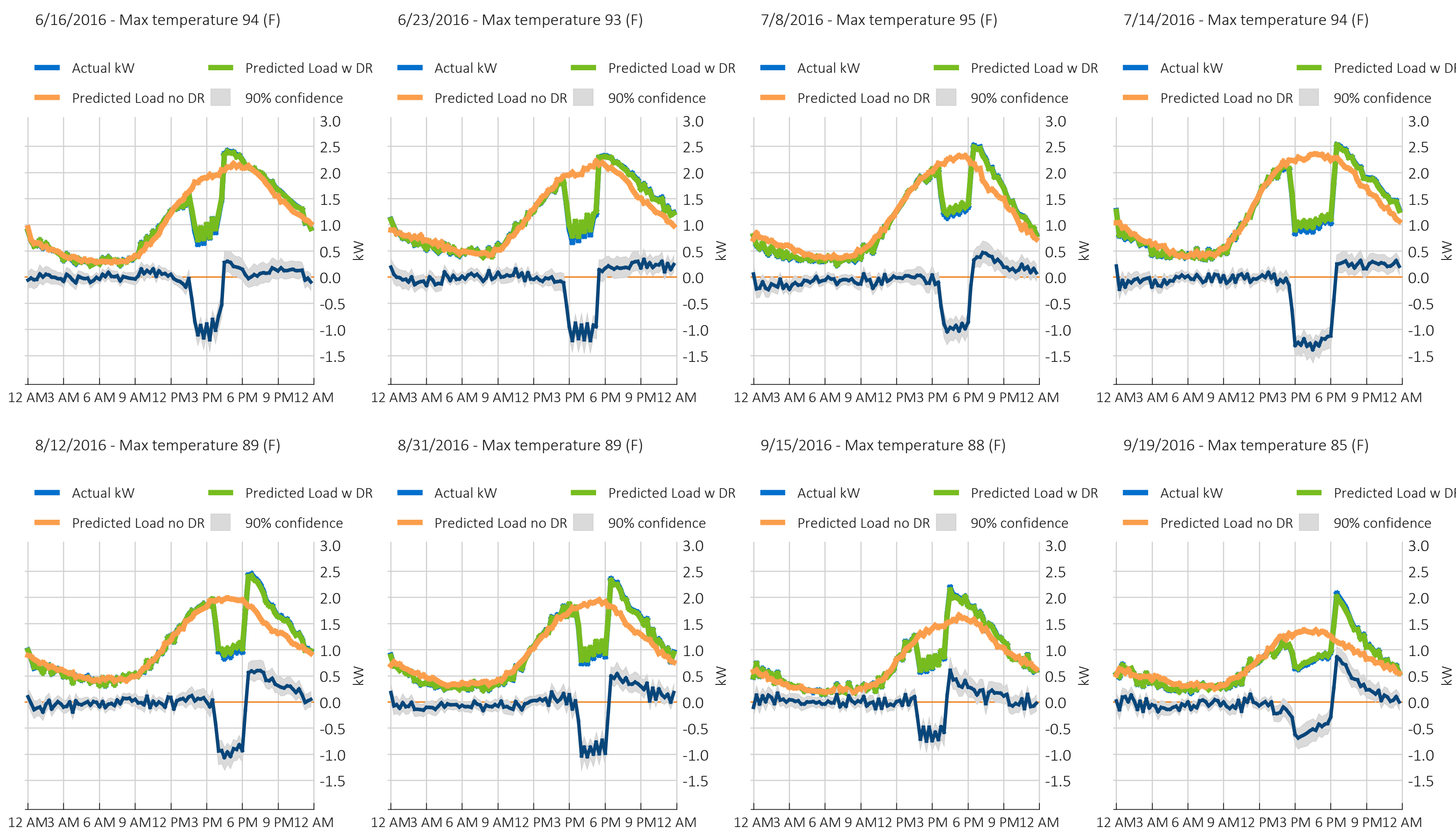
Average customer end use hourly load shapes and corresponding end use hourly impacts are shown for each 50% cycling event day in Figure 4-1. Average load shapes for each 64% cycling event days are shown in Figure 4-2. Average impacts for the 100% shed events are shown in Figure 4-3. The impacts shown in Figures 4-1 through 4-3 have been de-rated by 6.5% to account for the proportion of inoperable switch devices found by Nexant field staff among sampled participants in DEC territory.

Figure 4-1: Average End Use Load Impacts 50% Cycling Events



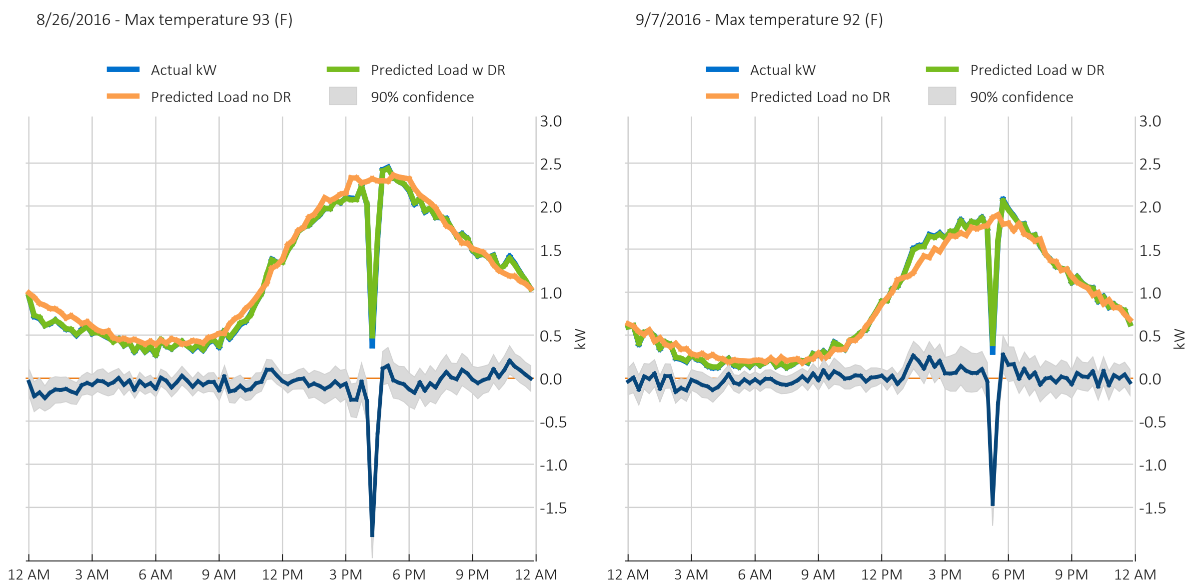

Impacts de-rated for inoperable devices (6.5%)

Figure 4-2: Average End Use Load Impacts 64% Cycling Events




Impacts de-rated for inoperable devices (6.5%)

Figure 4-3: Average End Use Load Impacts 100% Shed Events




Impacts de-rated for inoperable devices (6.5%)

## 4.2 Whole Building Results

The event day load impacts at the whole building level are presented in Table 4-2. The four 50% cycling events achieved an average load reduction of 0.65 kW, or approximately 20.3% of the 3.21 kW base load. The model found a 90% confidence band ranging from 0.49 kW to 0.81 kW. Among the eight 64% cycling events, the average impact was 0.88 kW, or approximately 26.4% of the 3.32 kW base load. Whole building impacts of 1.0 kW or more were achieved during four of these events. The two emergency 100% shed events achieved the largest impacts. The average impact for these events was 1.63 kW, or roughly 45.4% of the 3.59 average base load. The average impact for these events had a 90% confidence band ranging from 1.47 kW to 1.79 kW. Impacts shown in Table 4-2 represent the average load reduction during the duration of each event.

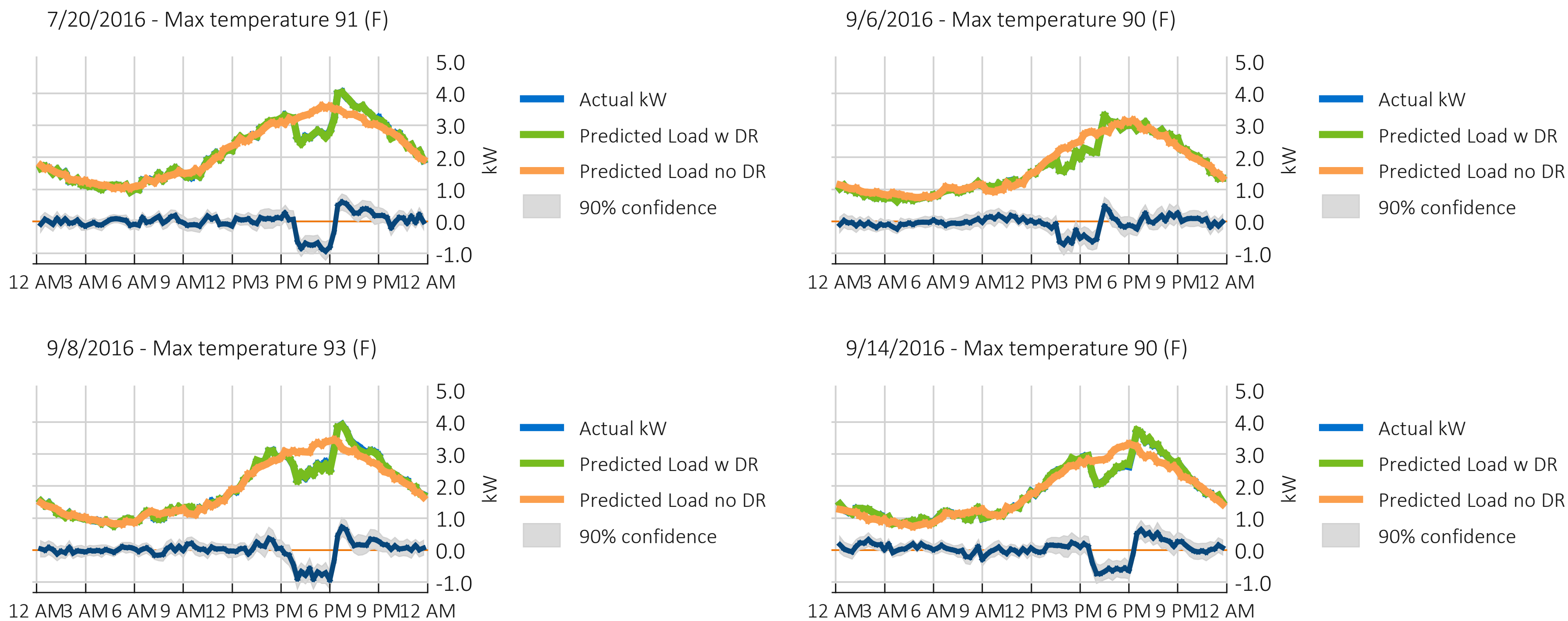
Table 4-2: Whole Building Event Day Load Impacts

| True Cycle | Date | Load without DR | Impact | Std. error | 90% Confidence Interval | | % Impact | 90% Confidence interval | | Daily Max (F) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower bound | Upper bound | | Lower Bound | Upper Bound | |
| 50% | 7/20/2016 | 3.59 | -0.76 | 0.16 | -0.50 | -1.02 | -21.1% | -13.9% | -28.4% | 91.0 |
| | 9/6/2016 | 2.68 | -0.51 | 0.18 | -0.21 | -0.80 | -18.9% | -7.8% | -30.0% | 90.3 |
| | 9/8/2016 | 3.37 | -0.73 | 0.18 | -0.44 | -1.03 | -21.8% | -13.1% | -30.5% | 93.0 |
| | 9/14/2016 | 3.19 | -0.61 | 0.17 | -0.33 | -0.89 | -19.0% | -10.2% | -27.8% | 90.7 |
| | **Average** | **3.21** | **-0.65** | **0.10** | **-0.49** | **-0.81** | **-20.3%** | **-15.4%** | **-25.3%** | **91.3** |
| 64% | 6/16/2016 | 3.30 | -1.00 | 0.17 | -0.72 | -1.28 | -30.3% | -21.8% | -38.8% | 94.0 |
| | 6/23/2016 | 3.46 | -1.05 | 0.17 | -0.77 | -1.32 | -30.2% | -22.2% | -38.2% | 94.0 |
| | 7/8/2016 | 3.94 | -1.01 | 0.16 | -0.74 | -1.28 | -25.7% | -18.9% | -32.4% | 95.2 |
| | 7/14/2016 | 3.85 | -1.20 | 0.16 | -0.93 | -1.47 | -31.2% | -24.3% | -38.1% | 95.7 |
| | 8/12/2016 | 3.36 | -0.87 | 0.16 | -0.60 | -1.14 | -25.9% | -18.0% | -33.9% | 89.7 |
| | 8/31/2016 | 3.39 | -0.89 | 0.16 | -0.63 | -1.15 | -26.2% | -18.6% | -33.8% | 90.0 |
| | 9/15/2016 | 2.62 | -0.54 | 0.18 | -0.25 | -0.83 | -20.7% | -9.6% | -31.8% | 89.0 |
| | 9/19/2016 | 2.64 | -0.46 | 0.17 | -0.19 | -0.74 | -17.5% | -7.0% | -27.9% | 86.7 |
| | **Average** | **3.32** | **-0.88** | **0.09** | **-0.72** | **-1.03** | **-26.4%** | **-21.8%** | **-31.1%** | **91.8** |
| 100% | 8/26/2016 | 3.75 | -1.72 | 0.16 | -1.46 | -1.99 | -45.9% | -38.8% | -53.0% | 93.9 |
| | 9/7/2016 | 3.44 | -1.54 | 0.16 | -1.28 | -1.80 | -44.8% | -37.2% | -52.3% | 91.7 |
| | **Average** | **3.59** | **-1.63** | **0.10** | **-1.47** | **-1.79** | **-45.4%** | **-40.9%** | **-49.9%** | **92.8** |

The four 50% true cycling events were called on days with daily maximum temperatures between 90.3°F and 93°F. Average per household hourly load shapes and corresponding hourly impacts are shown for each 50% cycling event day in Figure 4-4. Average load shapes for each 64% cycling event day are shown in Figure 4-5. Average impacts for the 100% shed events are shown in Figure 4-6. The impacts shown in Figure 4-4, Figure 4-5, and Figure 4-6 have been de-rated by 6.5% to account for the proportion of inoperable switch devices found by Nexant field staff among sampled participants in DEC territory.

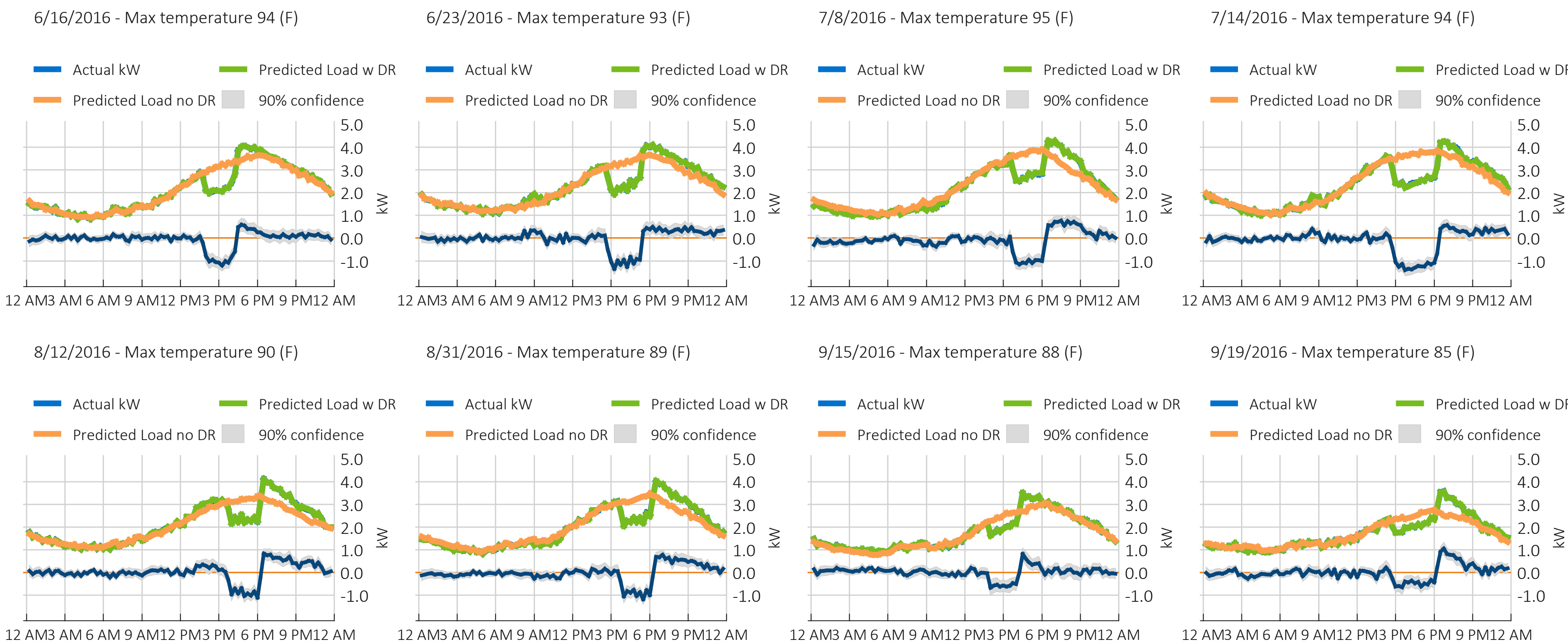
A total of eight 64% cycling events were called with daily maximum temperatures ranging from 86.7°F to 95.7°F. Hotter events occurred during the first half of the 2016 summer (June and July) with milder events being called in later summer months (August and September). Not surprisingly, greater impacts were shown during the earlier, hotter event days.

Figure 4-4: Average Whole Building Load Impacts 50% Cycling Events



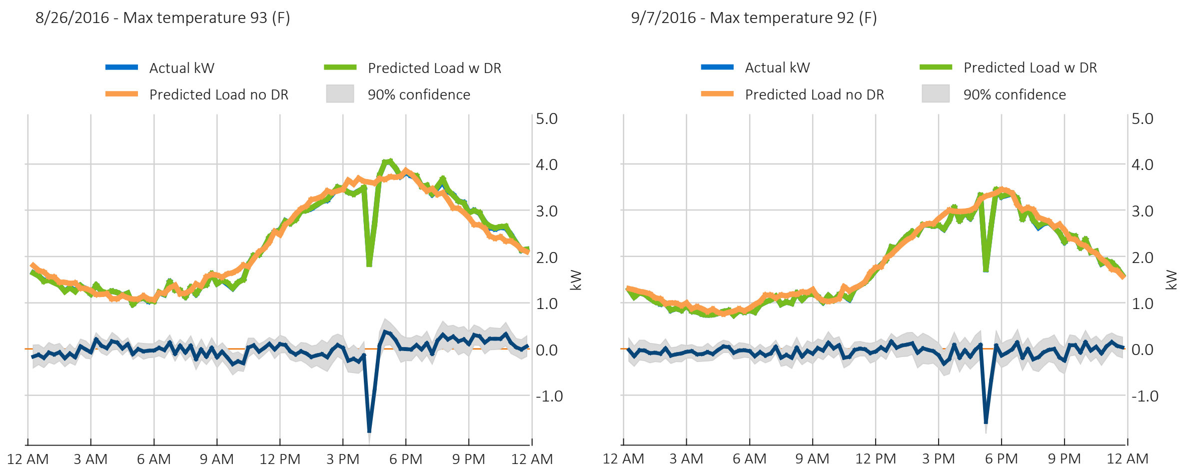

Impacts de-rated for inoperable devices (6.5%)

Figure 4-5: Average Whole Building Load Impacts 64% Cycling Events




Impacts de-rated for inoperable devices (6.5%)

Figure 4-6: Average Whole Building Load Impacts 100% Shed Events




Impacts de-rated for inoperable devices (6.5%)

## 4.3 Whole Building Versus End Use Impacts

Table 4-3 compares the impacts attained during each event called in 2016 at the whole building and end use levels. Average demand reductions were 0.65 kW, 0.88 kW, and 1.63 kW during the 50%, 64%, and 100% control events, respectively, at the whole house level, with larger impacts occurring on event days with higher temperatures. At the end use level, average impacts were 0.69 kW, 0.90, and 1.64 kW during the 50%, 64%, and 100% control events, respectively.

Table 4-3: Comparison of Whole Building Impacts vs. End Use Impacts

| True Cycle | Date | Event Start | Event End | Whole Building | | | End use (for household) | | | Daily Max °F |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Load without DR | Impact | % Impact | Load without DR | Impact | % Impact | |
| 50% | 7/20/2016 | 3:30 PM | 6:00 PM | 3.59 | -0.76 | -21.1% | 1.98 | -0.75 | -38.0% | 91.0 |
| | 9/6/2016 | 3:30 PM | 6:00 PM | 2.68 | -0.51 | -18.9% | 1.47 | -0.52 | -35.6% | 90.3 |
| | 9/8/2016 | 1:30 PM | 4:00 PM | 3.37 | -0.73 | -21.8% | 1.95 | -0.83 | -42.5% | 93.0 |
| | 9/14/2016 | 3:30 PM | 6:00 PM | 3.19 | -0.61 | -19.0% | 1.68 | -0.66 | -39.4% | 90.7 |
| | **Average** | **N/A** | **N/A** | **3.21** | **-0.65** | **-20.3%** | **1.77** | **-0.69** | **-39.1%** | **91.3** |
| 64% | 6/16/2016 | 2:30 PM | 5:00 PM | 3.30 | -1.00 | -30.3% | 1.91 | -0.98 | -51.4% | 94.0 |
| | 6/23/2016 | 2:30 PM | 6:00 PM | 3.46 | -1.05 | -30.2% | 2.03 | -1.05 | -51.7% | 94.0 |
| | 7/8/2016 | 2:30 PM | 6:00 PM | 3.94 | -1.01 | -25.7% | 2.28 | -0.96 | -42.1% | 95.2 |
| | 7/14/2016 | 1:30 PM | 4:00 PM | 3.85 | -1.20 | -31.2% | 2.30 | -1.24 | -53.9% | 95.7 |

| True Cycle | Date | Event Start | Event End | Whole Building | | | End use (for household) | | | Daily Max °F |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Load without DR | Impact | % Impact | Load without DR | Impact | % Impact | |
| | 8/12/2016 | 3:30 PM | 6:00 PM | 3.36 | -0.87 | -25.9% | 1.96 | -0.94 | -48.0% | 89.7 |
| | 8/31/2016 | 3:30 PM | 6:00 PM | 3.39 | -0.89 | -26.2% | 1.90 | -0.90 | -47.5% | 90.0 |
| | 9/15/2016 | 3:30 PM | 6:00 PM | 2.62 | -0.54 | -20.7% | 1.40 | -0.60 | -42.9% | 89.0 |
| | 9/19/2016 | 1:30 PM | 4:00 PM | 2.64 | -0.46 | -17.5% | 1.33 | -0.51 | -38.6% | 86.7 |
| | **Average** | **N/A** | **N/A** | **3.32** | **-0.88** | **-26.4%** | **1.89** | **-0.90** | **-47.6%** | **91.8** |
| 100% | 8/26/2016 | 4:00 PM | 4:20 PM | 3.75 | -1.72 | -45.9% | 2.32 | -1.82 | -78.7% | 93.9 |
| | 9/7/2016 | 5:00 PM | 5:20 PM | 3.44 | -1.54 | -44.8% | 1.87 | -1.46 | -78.2% | 91.7 |
| | **Average** | **N/A** | **N/A** | **3.59** | **-1.63** | **-45.4%** | **2.09** | **-1.64** | **-78.5%** | **92.8** |

* Load impacts reported exclude the first half hour when air conditioner control is randomly phased in.

The following set of graphics provides visual comparisons of the average hourly impacts derived from the regression analysis for each DEC Power Manager event. The key takeaway from Table 4-3, Figure 4-7, and Figure 4-8 is that, while slight deviations occur, the magnitude of the impacts shown by the whole building analysis vs. end use analysis are within the margin of estimation error. As discussed previously, this indicates that customers do not compensate for Power Manager's air conditioner curtailments through other end uses.

Figure 4-7 compares load impacts derived from whole building data vs. those derived from end use data for each of the eight 64% cycling events. In general, events called under hotter temperatures achieve greater load reductions. Results show that per household impacts of 1.0 kW or greater are achievable under hotter temperature conditions.

Figure 4-8 compares load impacts derived from whole building data vs. those derived from end use data for each of the four 50% cycling events (7/20/2016, 9/6/2016, 9/8/2016, and 9/14/2016) as well as for the two 100% shed events (8/26/2016 and 9/7/2016).

Figure 4-7: Comparison of Whole Building vs. End Use Impacts for 64% Load Cycling Events

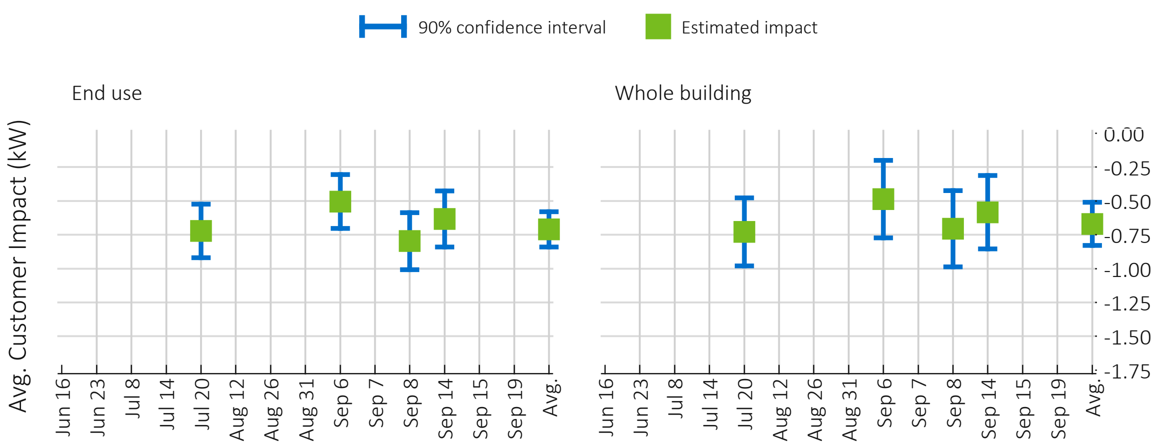

Whole building and end use regression impacts de-rated for inoperable devices (6.5%)

Figure 4-8: Comparison of Whole Building vs. End Use Impacts for 50% and 100% Control Events


Whole building and end use regression impacts de-rated for inoperable devices (6.5%)

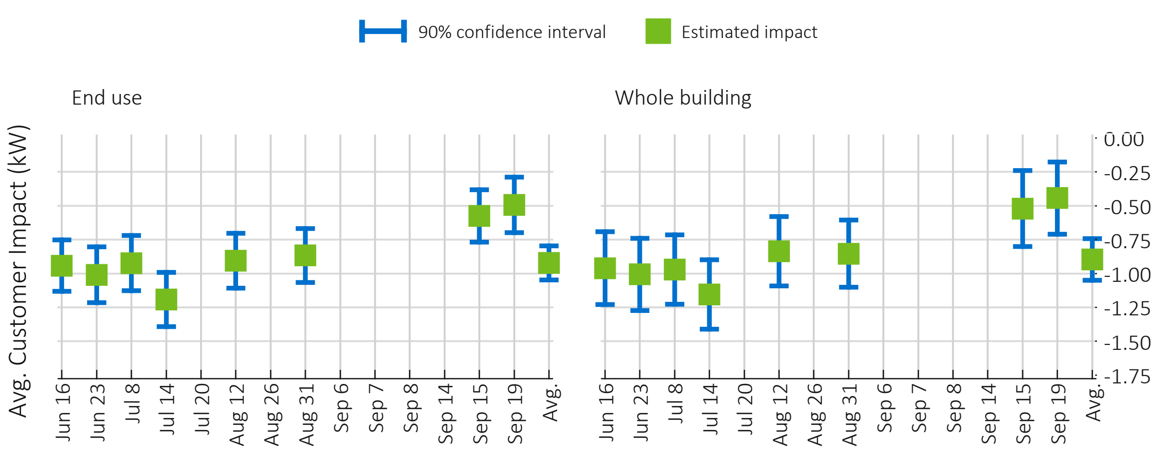
Figure 4-9, Figure 4-10, and Figure 4-11 show comparisons of end use vs. whole building load impacts for each event under 50% cycling, 64% cycling, and 100% shed, respectively. These plots show the point estimates for load reduction on each event day, along with the 90% confidence intervals. As a rule of thumb, the whole building impacts have slightly wider confidence intervals than the end use impacts due to additional noise in the whole building data stemming from other end uses that are captured by the whole building measurements. The figures show that differences between the whole building and end use load impact estimates for each event day fall within the range of estimation uncertainty, and are thus statistically similar to one another.

Figure 4-9: Comparison of Whole Building and End Use Impacts 50% Cycling Events



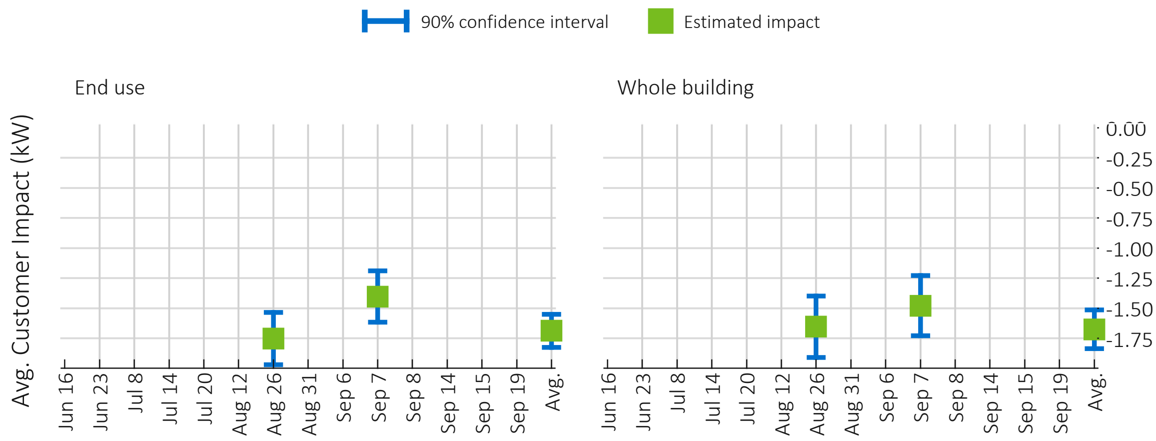

Impacts de-rated for inoperable devices (6.5%)

Figure 4-10: Comparison of Whole Building and End Use Impacts 64% Cycling Events




Impacts de-rated for inoperable devices (6.5%)

Figure 4-11: Comparison of Whole Building and End Use Impacts 100% Shed Events



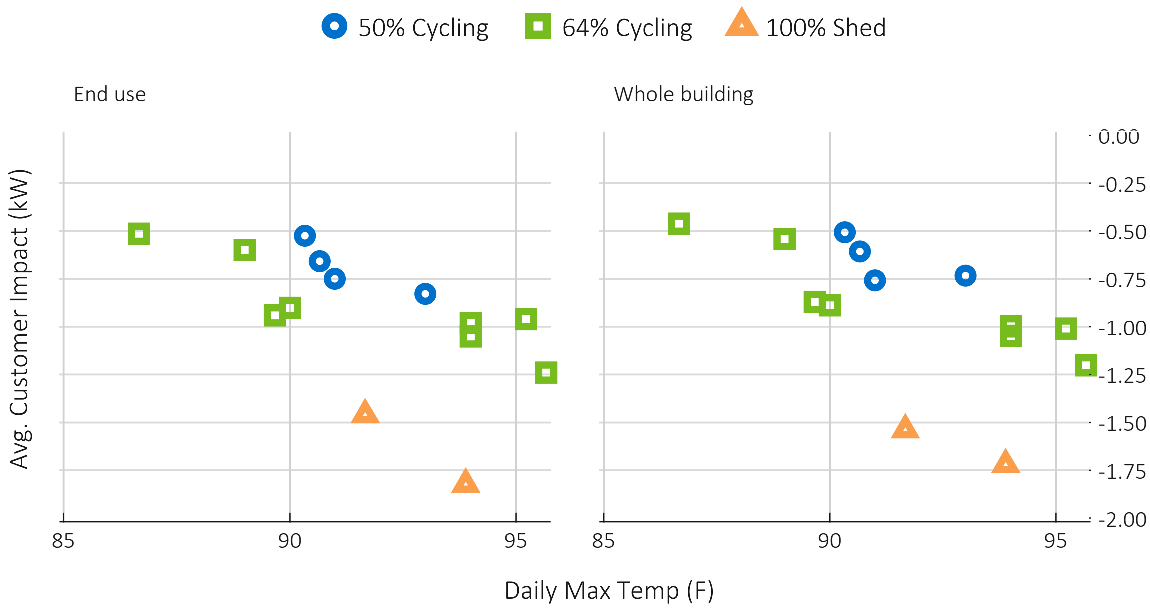

Impacts de-rated for inoperable devices (6.5%)

## 4.4 Weather Sensitivity

Power Manager load reductions grow with hotter weather and with deeper cycling. The program delivers larger demand reductions precisely when resources are needed most. Average load impacts during each event are shown in Figure 4-12 as a function of daily maximum temperature. Impacts are broken down by cycling option and are shown at the end use and whole building level. Again, these results show that the sensitivity to temperature change is very similar between whole building and end use impacts. On hotter days (above 93°F), impacts exceeded 1.0 kW for 64% and 100% control. Furthermore, while the trend or larger reductions with hotter weather is clear for 100% shed events and 64% cycling impacts, the trend is less clear for 50% cycling due to having only four events under a limited range of temperatures.

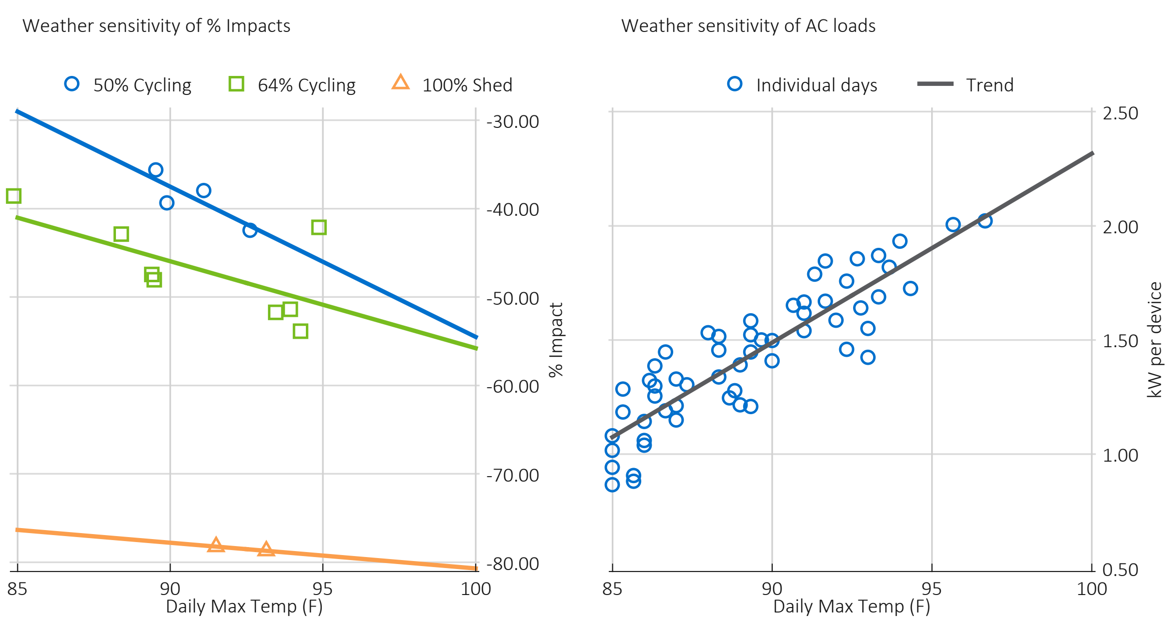
The larger demand reductions with hotter weather are both due to larger air conditioning demand and due to larger percent reductions. This can be seen in Figure 4-13. The panel on the left shows the 2016 end use air conditioner percent demand reductions, while the panel on the right shows 2016 air conditioner demand per unit for the 4 to 6pm period of nonevent days. While 2016 did not experience 102˚F conditions, the data relationship between percent reductions and weather and air conditioner loads and weather can be used to produce an estimate of demand reduction capability for planning purposes.

Figure 4-12: 2016 Load Reductions by Cycling Level as a Function of Temperature and Control Strategy




Impacts de-rated for inoperable devices (6.5%)

Figure 4-13: Both Air Conditioning Loads and Percent Demand Reductions are Weather Sensitive




Regression impacts de-rated for inoperable devices (6.5%)

Actual 2016 AC loads per unit on non-event weekdays

## 4.5 Key Findings

A few key findings are worth highlighting:

- Demand reductions at the end use level were 0.69 kW for the average 50% cycling event, 0.90 for the average 64% cycling event, and 1.64 kW for the average 100% shed event.
- Demand reductions at the whole house level were 0.65 kW per household for the average 50% cycling event, 0.88 kW for the 64% cycling event, and 1.63 kW for the 100% shed event.
- Impacts grow larger in magnitude when temperatures are hotter and more AC loads are available for curtailment.
- There is a clear relationship between weather, degree of load cycling control, and the magnitude of impacts.
- During hotter conditions, reductions exceeding 1.0 kW per participant are attainable with 64% and 100% control.
- There is no evidence that customers compensate for air conditioner curtailments by increasing other end uses—whole building impacts are indistinguishable from end use impacts.

# 5 Demand Reduction Capability—Time-Temperature Matrix

A key objective of the 2016 evaluation was to quantify the relationship between demand reductions, temperature, hour of day, and cycling strategy—referred to as the time-temperature matrix. By design, a large number of events were called under different weather conditions, for different dispatch windows, using various cycling strategies so that demand reduction capability could be estimated for a wide range of operating and planning conditions.

Weather conditions vary substantially from year to year as shown earlier in Figure 2-3. Because 2016 conditions did not approach the 102˚F conditions Duke Carolinas has previously experienced multiple times, the reductions capability had to be estimated based on the data available.

## 5.1 Methodology

Figure 5-1 was introduced earlier, but is worth revisiting because it illustrates the essential trends and challenges. Not only do Power Manager demand reductions grow on a percentage basis with hotter weather and with deeper cycling, but so do the air conditioner loads available for curtailment. The implication is that larger percent reductions are attainable from larger loads when temperatures are hotter. However, producing estimates of the reduction capability for 102˚F, unavoidably requires extrapolation of patterns observed in 2016 to conditions that were hotter than those experienced in 2016.

Figure 5-1: Both Air Conditioning Loads and Percent Demand Reductions are Weather Sensitive

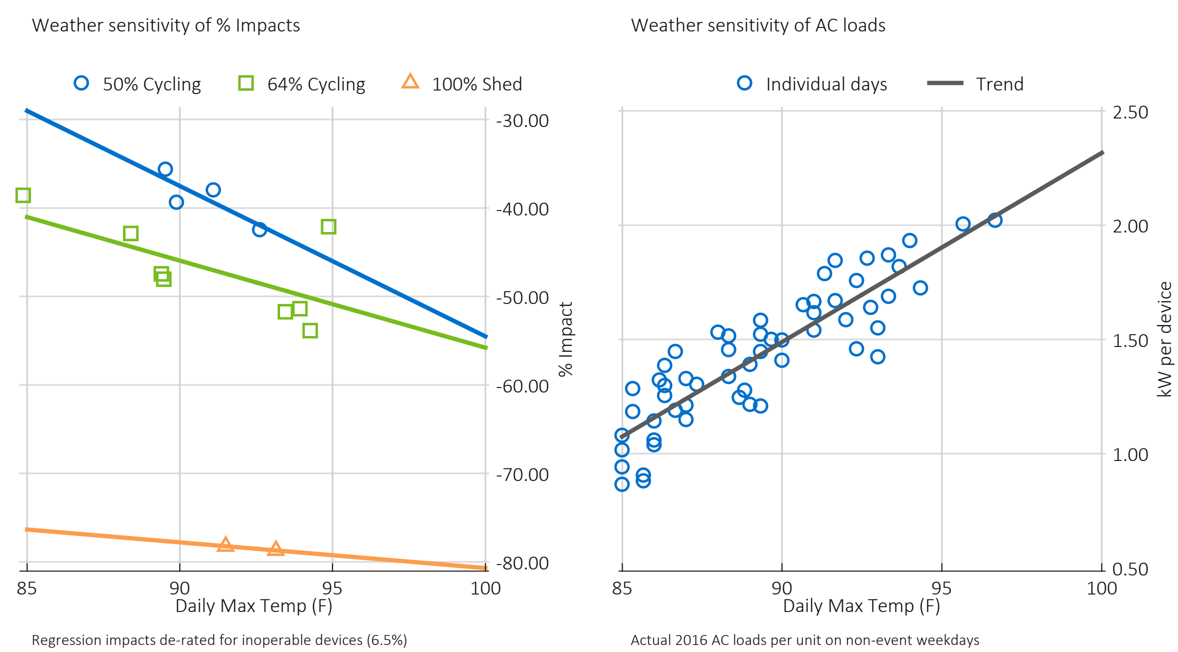


Figure 5-2: Time Temperature Matrix Development Process

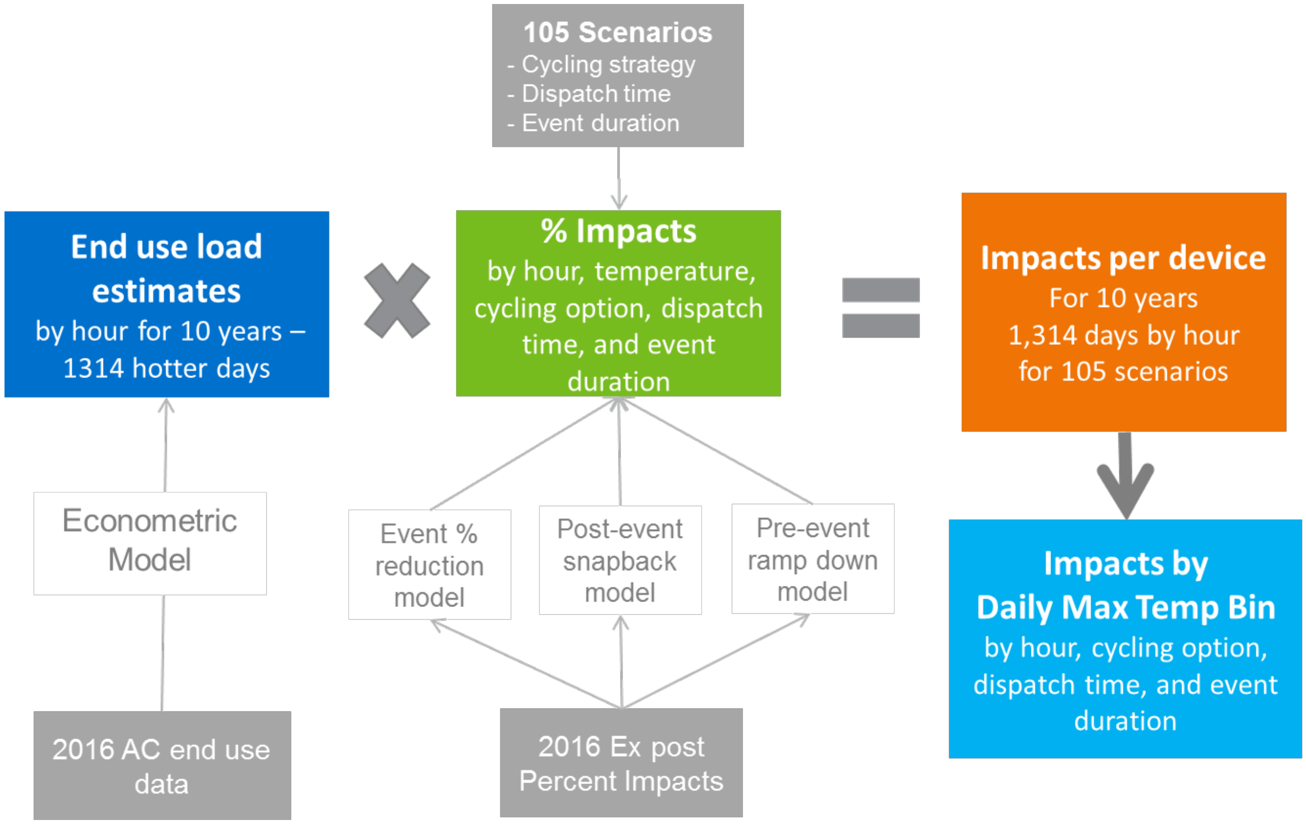



Figure 5-2 illustrates the process used to estimate the demand reduction capability under various conditions:

- Estimates of air conditioner loads were developed using the 2016 air conditioner end use data and using the same regression models used to estimate impacts. All weekdays with daily maximum temperatures above 75˚F were included in the models. The models were used to estimate air conditioner load patterns for 1,314 days in 10 years. Because the models were based on 2016 data, they reflect current usage patterns and levels of efficiency. The 2016 air conditioner patterns were applied to actual weather patterns experienced in past 10 years and not hypothetical weather patterns.
- Estimates of the percent reductions were based on three distinct econometric models of load control phase in, percent reductions during the event, and post-event snapback. The models were based on the percent impacts and temperatures experienced during 2016 events.
- A total of 105 scenarios were develop to reflect various cycling/control strategies, event dispatch times, and event lengths.
- Estimated impacts per device were produced. This was done by combining the estimated air conditioner loads, estimated percent reductions, and dispatch scenarios. The process produced estimated hourly impacts for each of 1,314 hotter weekdays in 2006-2016 under 105 scenarios each.

- Multiple days in narrow temperature bins were averaged to produce an expected reduction profile. Days with the similar daily maximum temperature can have distinct temperature profiles and the heat buildup influenced the amount of air conditioner load.

## 5.2 Demand Reduction Capability for 102˚F Conditions

While Power Manager is typically dispatched for economic reasons or research, its primary purpose is to deliver demand relief during extreme conditions when demand is high and capacity is constrained. Since 2006, Duke Energy Carolinas has experienced 5 weekdays and 2 weekend days when system temperatures reached 100˚F or more. Several of these days occurred in 2007, when on the hottest weekday system temperatures reached 103˚F. Extreme temperature conditions can trigger Power Manager emergency operations where all devices are instructed to instantaneously shed loads and deliver larger demand reductions than normal cycling events (100% emergency shed). While emergency operations are rare and ideally avoided, they represent the full demand reduction capability of Power Manager.

Figure 5-3: Demand Reduction Capability on a 102˚F with 100% Emergency Shed

| INPUTS | |
|---|---|
| True Cycle | 100 |
| Event start (excludes phase in) | 4 PM |
| Event duration | 1 |
| Daily Max Temp (F) | 102 |
| Devices | 229,000 |

| Event Window Avg. Impacts | | |
|---|---|---|
| Load without DR | 2.35 | kW per device |
| Load with DR | 0.49 | kW per device |
| Impact per device | -1.8652 | kW per device |
| Impact (MW) | -427.1 | MW |
| % Impact | -79.3% | % |

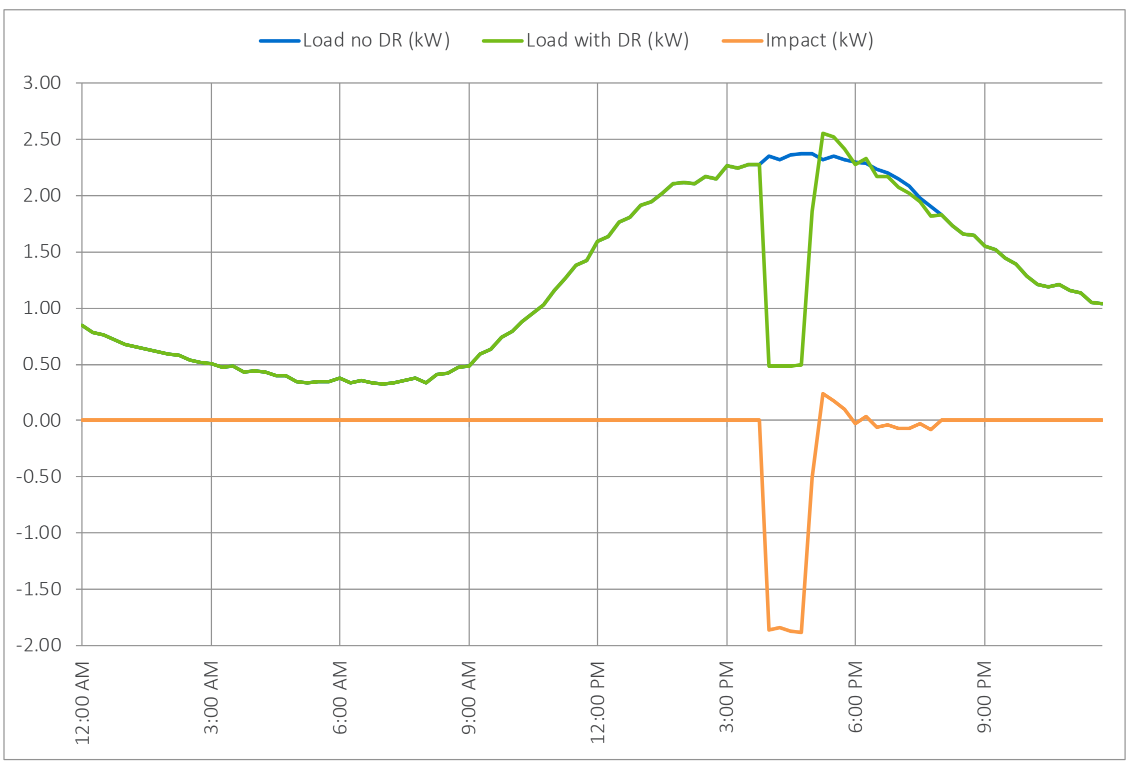


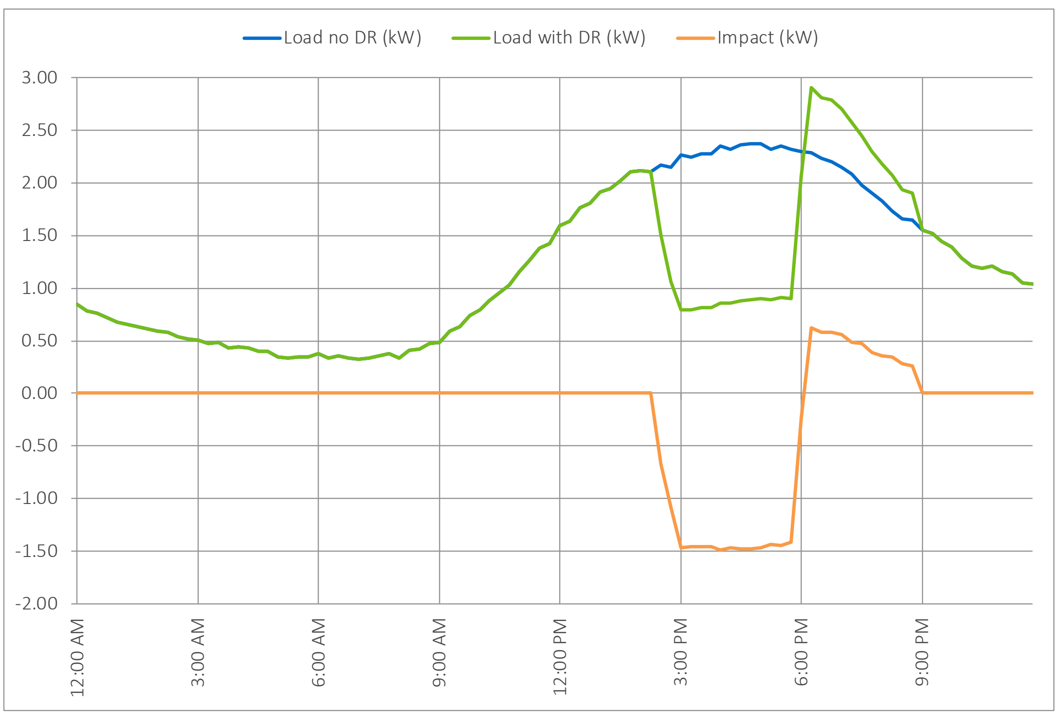
Figure 5-3 shows the demand reduction capability of the program if 100% shed becomes necessary on a 102˚F day for a single hour. Individual air conditioner units are expected to deliver 1.87 kW of demand reduction or 2.22 kW per household (on average Power Manager participants have 1.19 units). Because there are approximately 229,000 devices, the expected aggregate reductions total is 427.1 MW.[7]

Power Manager can deliver substantial demand reductions under 102˚F conditions, even if emergency shed operations are not employed and non-emergency dispatch is employed. With a three hour 64% cycling event, demand reductions average 334.2 MW across the dispatch hours, as shown in Figure 5-4. With longer events, reductions vary slightly across fifteen minute intervals but are generally larger when air conditioner use is highest. The reduction capability is lowest, averaging 202.9 MW across three dispatch hours, when less extensive load control strategies, such as 50% cycling, are employed, as show in Figure 5-5

Figure 5-4: Demand Reduction Capability on a 102˚F with 64% Cycling

| INPUTS | |
|---|---|
| True Cycle | 64 |
| Event start (excludes phase in) | 3 PM |
| Event duration | 3 |
| Daily Max Temp (F) | 102 |
| Devices | 229,000 |

| Event Window Avg. Impacts | | |
|---|---|---|
| Load without DR | 2.32 | kW per device |
| Load with DR | 0.86 | kW per device |
| Impact per device | -1.4596 | kW per device |
| Impact (MW) | -334.2 | MW |
| % Impact | -62.9% | % |

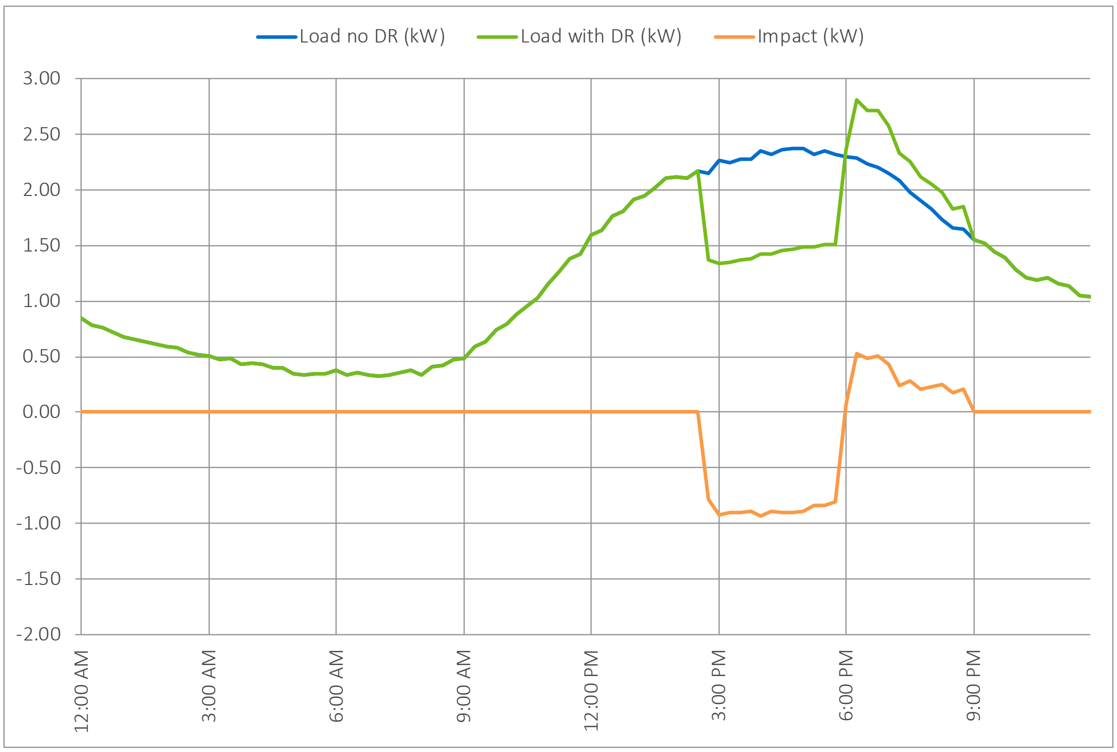



[7] Aggregate impacts are presented throughout the report without rounding error. For example, while 1.87 kW x 229,000 devices equals 428.2 MW, the more granular impacts per device, 1.8652 kW per device were used to estimate aggregate impacts of 427.1 MW (1.8652 kW x 229,000 devices).

Figure 5-5: Demand Reduction Capability on a 102˚F using 50% Cycling

| INPUTS | |
|---|---|
| True Cycle | 50 |
| Event start (excludes phase in) | 3 PM |
| Event duration | 3 |
| Daily Max Temp (F) | 102 |
| Devices | 229,000 |

| Event Window Avg. Impacts | | |
|---|---|---|
| Load without DR | 2.32 | kW per device |
| Load with DR | 1.43 | kW per device |
| Impact per device | -0.8859 | kW per device |
| Impact (MW) | -202.9 | MW |
| % Impact | -38.2% | % |




## 5.3 Demand Reduction Capability by Temperature, Cycling Strategy, and Event Start Time

Table 5-1 summarizes the estimated demand reduction for 100% emergency shed by event start time, and daily maximum system temperature, assuming a one hour event. Table 5-2 summarizes similar information for non-emergency dispatch operations assuming a three hour event. Most non-emergency operations start at 3pm or 4 pm. All estimated impacts exclude the 30 minute periods when the 64% and 50% cycling are randomly phased in and phased out. In practice, event day impacts may vary due to unique weather patterns or day characteristics.

Table 5-1: Emergency Shed Per Device Demand Impacts by Temperature and Event Start

| True Cycle | Daily Max (F) | Start Time (1 Hour Event)* | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 12 PM | 1 PM | 2 PM | 3 PM | 4 PM | 5 PM | 6 PM |
| 100 | 74 | -0.16 | -0.20 | -0.25 | -0.26 | -0.28 | -0.30 | -0.28 |
| | 76 | -0.21 | -0.27 | -0.34 | -0.37 | -0.40 | -0.41 | -0.38 |
| | 78 | -0.22 | -0.28 | -0.37 | -0.41 | -0.44 | -0.46 | -0.42 |
| | 80 | -0.28 | -0.37 | -0.47 | -0.52 | -0.55 | -0.56 | -0.53 |
| | 82 | -0.34 | -0.45 | -0.57 | -0.63 | -0.68 | -0.69 | -0.65 |
| | 84 | -0.45 | -0.58 | -0.69 | -0.75 | -0.80 | -0.80 | -0.74 |
| | 86 | -0.56 | -0.71 | -0.82 | -0.89 | -0.93 | -0.93 | -0.87 |
| | 88 | -0.69 | -0.84 | -0.96 | -1.02 | -1.06 | -1.05 | -0.99 |
| | 90 | -0.77 | -0.94 | -1.06 | -1.13 | -1.17 | -1.15 | -1.08 |
| | 92 | -0.91 | -1.09 | -1.21 | -1.27 | -1.29 | -1.26 | -1.18 |
| | 94 | -1.01 | -1.19 | -1.31 | -1.37 | -1.40 | -1.38 | -1.31 |
| | 96 | -1.14 | -1.33 | -1.45 | -1.51 | -1.54 | -1.53 | -1.45 |
| | 98 | -1.19 | -1.41 | -1.53 | -1.60 | -1.64 | -1.62 | -1.53 |
| | 100 | -1.34 | -1.57 | -1.70 | -1.79 | -1.83 | -1.81 | -1.70 |
| | 102 | -1.35 | -1.59 | -1.69 | -1.80 | -1.87 | -1.86 | -1.79 |

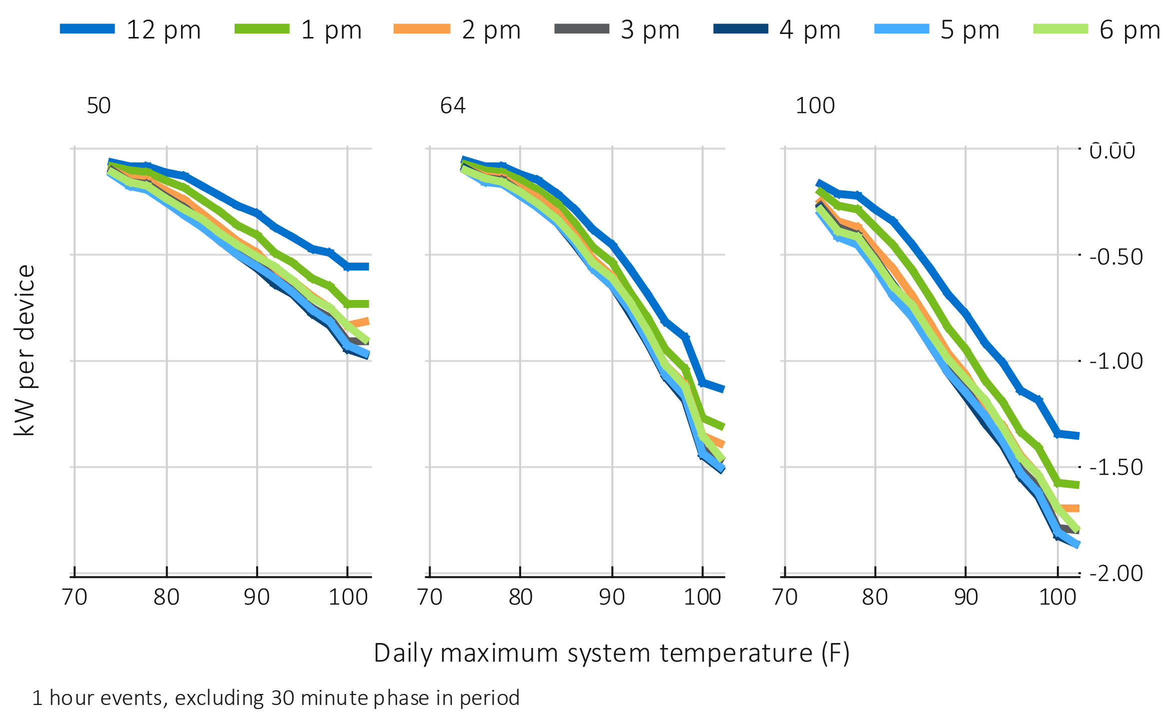
Table 5-2: Non-Emergency Dispatch Per Device Demand Impacts by Temperature and Event Start

| True Cycle | Daily Max (F) | Start Time (3 Hour Event)* | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 12 PM | 1 PM | 2 PM | 3 PM | 4 PM | 5 PM | 6 PM |
| 50 | 74 | -0.07 | -0.08 | -0.09 | -0.10 | -0.10 | -0.10 | -0.10 |
| | 76 | -0.09 | -0.12 | -0.14 | -0.15 | -0.15 | -0.14 | -0.13 |
| | 78 | -0.10 | -0.13 | -0.15 | -0.17 | -0.17 | -0.16 | -0.14 |
| | 80 | -0.13 | -0.17 | -0.20 | -0.22 | -0.22 | -0.20 | -0.18 |
| | 82 | -0.17 | -0.21 | -0.25 | -0.28 | -0.28 | -0.26 | -0.23 |
| | 84 | -0.21 | -0.27 | -0.31 | -0.33 | -0.33 | -0.30 | -0.26 |
| | 86 | -0.27 | -0.33 | -0.37 | -0.39 | -0.39 | -0.36 | -0.31 |
| | 88 | -0.32 | -0.39 | -0.43 | -0.46 | -0.45 | -0.41 | -0.35 |
| | 90 | -0.37 | -0.44 | -0.49 | -0.51 | -0.50 | -0.46 | -0.39 |
| | 92 | -0.44 | -0.52 | -0.56 | -0.58 | -0.56 | -0.51 | -0.43 |
| | 94 | -0.48 | -0.56 | -0.61 | -0.63 | -0.62 | -0.57 | -0.48 |
| | 96 | -0.55 | -0.64 | -0.69 | -0.71 | -0.70 | -0.64 | -0.54 |
| | 98 | -0.58 | -0.68 | -0.74 | -0.76 | -0.75 | -0.69 | -0.58 |
| | 100 | -0.65 | -0.77 | -0.84 | -0.87 | -0.85 | -0.76 | -0.64 |
| | 102 | -0.65 | -0.76 | -0.84 | -0.89 | -0.88 | -0.82 | -0.69 |
| 64 | 74 | -0.07 | -0.08 | -0.08 | -0.09 | -0.09 | -0.09 | -0.09 |
| | 76 | -0.10 | -0.11 | -0.13 | -0.14 | -0.14 | -0.13 | -0.12 |
| | 78 | -0.10 | -0.12 | -0.14 | -0.15 | -0.15 | -0.14 | -0.13 |
| | 80 | -0.14 | -0.17 | -0.19 | -0.20 | -0.20 | -0.19 | -0.18 |
| | 82 | -0.18 | -0.22 | -0.24 | -0.26 | -0.26 | -0.25 | -0.22 |
| | 84 | -0.25 | -0.29 | -0.32 | -0.33 | -0.33 | -0.31 | -0.28 |
| | 86 | -0.33 | -0.38 | -0.41 | -0.43 | -0.42 | -0.40 | -0.36 |
| | 88 | -0.44 | -0.49 | -0.52 | -0.54 | -0.53 | -0.51 | -0.46 |
| | 90 | -0.51 | -0.57 | -0.61 | -0.62 | -0.62 | -0.59 | -0.53 |
| | 92 | -0.64 | -0.70 | -0.74 | -0.75 | -0.73 | -0.69 | -0.63 |
| | 94 | -0.76 | -0.83 | -0.87 | -0.88 | -0.87 | -0.83 | -0.76 |
| | 96 | -0.90 | -0.98 | -1.02 | -1.04 | -1.03 | -0.98 | -0.90 |
| | 98 | -0.99 | -1.07 | -1.12 | -1.14 | -1.13 | -1.08 | -0.98 |
| | 100 | -1.21 | -1.32 | -1.38 | -1.40 | -1.38 | -1.31 | -1.19 |
| | 102 | -1.25 | -1.36 | -1.42 | -1.46 | -1.46 | -1.40 | -1.28 |

*Estimates exclude 30 minute phase in period and reflect the average reduction expected for the event

Figure 5-6 provides a visual summary of the reduction capability for a one hour event by cycling strategy and start time. As expected, reductions are larger with hotter temperatures and more aggressive load control operations. The start time also influences the magnitude of reductions which, generally, are larger during hours when air conditioner loads are highest. Appendix B includes the demand reduction capability for a range of event durations.

Figure 5-6: Per Device Demand Impacts by Cycling Strategy, Temperature Conditions, and Event Start




## 5.4 Key Findings

Key findings from the development of the time temperature matrix include:

- While emergency operations are rare and ideally avoided, they represent the full demand reduction capability of Power Manager;
- Not only do Power Manager demand reductions grow on a percentage basis with hotter weather and with deeper cycling, but so do the air conditioner loads available for curtailment;
- If 100% emergency shed becomes necessary on a 102˚F day, Power Manager can deliver 1.87 kW of demand reductions per device or 2.22 kW per household;
- Because there are approximately 229,000 devices, the expected aggregate reductions total 427.1 MW;
- Reductions are larger with hotter temperatures and more aggressive load control operations; and
- The event start time also influences the magnitude of reductions which, generally, are larger during hours when air conditioner loads are highest.

# 6 Device Operability and Site Level Performance

A significant problem in load control programs is nonperforming devices or sites. This can be due to broken or disconnected control devices, or devices failing to receive control event paging signals. It also can occur because of broken air conditioner units or because some customers do not use their air conditioners during event hours. Due to the significant cost of direct verification of device operation, utilities often assume a customer remains a part of the program without any ongoing verification. It is not financially feasible to blindly send service technicians to every property to check device operation. Until recently, with no way to identify broken devices, it has been easier and more cost effective to recruit new customers. If DEC is able to remotely identify sites that underperform because of broken or missing devices or because of paging network communication failures, it could increase the aggregate impacts of the program without as much cost as new customer acquisition.

Using 15 minute interval data from DEC's air conditioning cycling load control program, Nexant undertook the task of creating methods to identify probable inoperable or missing devices. Our effort involved two main steps:

- A field study designed to physically test whether load control devices were functional. The main purpose of this study component was to quantify the share of inoperable devices. This estimate, however, does not factor in paging network communication failures or sites that do not have their air conditioner on during event hours. As described later in this report, the incidence rate is one of the critical components affecting the precision of efforts to identify broken or missing devices.
- Use of data analytics to develop methods that identify sites that underperform or that do not deliver demand reductions. A device that is not functional does not reduce air conditioner demand over multiple events.

The field study was implemented in tandem with the installation of air conditioner data loggers and served to quantify the device failure base rate. While data analytics was used to identify underperforming sites, a separate verification test to determine the precision of the diagnosis has not yet been implemented. Nexant's expectation is that using whole building smart meter data to identify nonperforming or missing devices will lead to substantial improvements over blindly sending technicians to assess device performance. These efforts, however, are most precise if they are restricted to households that clearly use air conditioners during hotter weather conditions. These customers also offer greater impact potential since they use air conditioners during peak conditions. Diagnosis of nonperforming devices is less accurate when it is applied to sites with low or no air conditioner use during peak hours of hotter days.

## 6.1 Device Operability Field Test

As part of the study, Nexant was responsible for all field work related to customer recruitment for end-use data collection as well as installation and collection of data loggers. Customers were recruited from a random sample of the Power Manager participant population. Prior to installing data loggers on air conditioners, Nexant tested whether load control devices were functional. The inspection consisted of:

- Onsite spot measurements of the kW, voltage, amperage, and power factor;

- Information about the AC unit;
- Inspection of the load control device for presence, proper installation, physical condition, and operability; and
- Inspection of the load control device connection wires, including presence, physical condition, and whether the connection was secure.

Because data quality is essential for accurate program evaluation, Nexant ensured that all site visits related to logger installations/retrievals were carefully planned and executed by trained technicians having appropriate experience. Nexant field engineers installed loggers only on systems having operable switches. The rigor taken to assess device operability prior to logger installation is described in Section 3.6 of this report. Results of onsite device operability checks are based on inspections during logger installations in March 2016 and are summarized in Table 6-1.

Based on field tests, 144 out of the 154 devices tested, 93.5%, of devices are operable, with a 90% confidence interval of ±3.27%. This does not account for devices that do not perform due to paging network issues or because the air conditioner is not in use during afternoon peak hours of hotter days.

Table 6-1: End Use Logger Device Operability

| Metric | Value |
|---|---|
| Devices inspected | 154 |
| Inoperable devices | 10 |
| Operable devices (i.e., loggers installed) | 144 |
| Device failure rate | 6.5% |

## 6.2 Results

Figure 6-1 illustrates the six prototypical load shapes produced by the cluster analysis. The shapes for customers in groups 2, 3, and 5 suggest a distinct load drop. Customers in group 6 have a smaller but still distinct load drop. The shapes for groups 1 and 4 suggest no load reduction took place for these customers during events despite the automation. This could be due to missing or failing devices, paging network gaps, or lack of air conditioner loads.

Figure 6-1: Prototypical Event Load Shapes

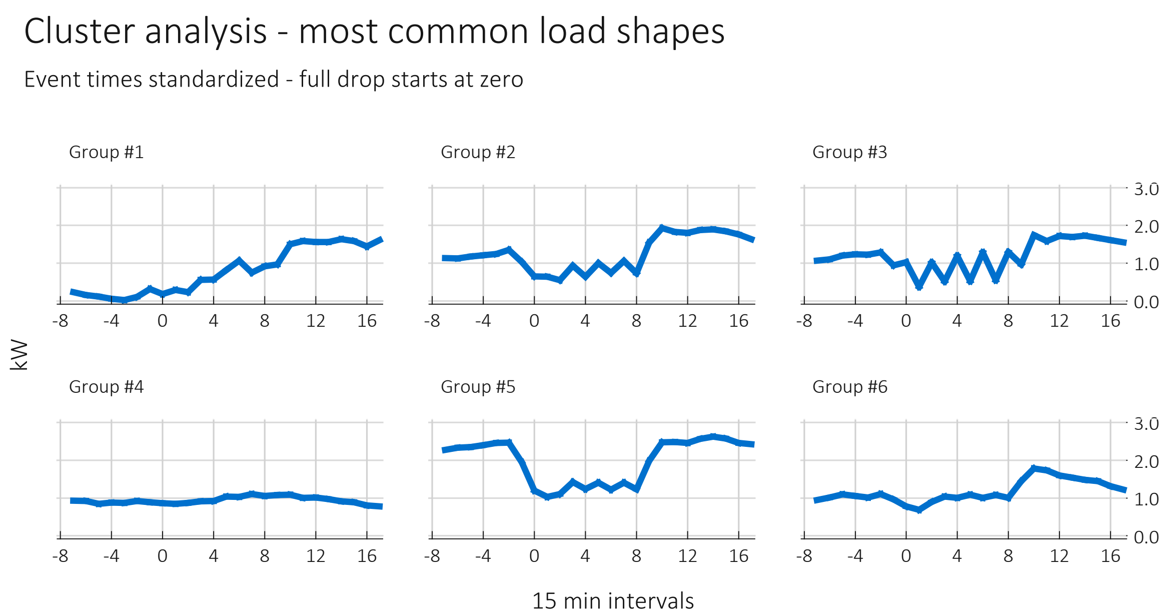
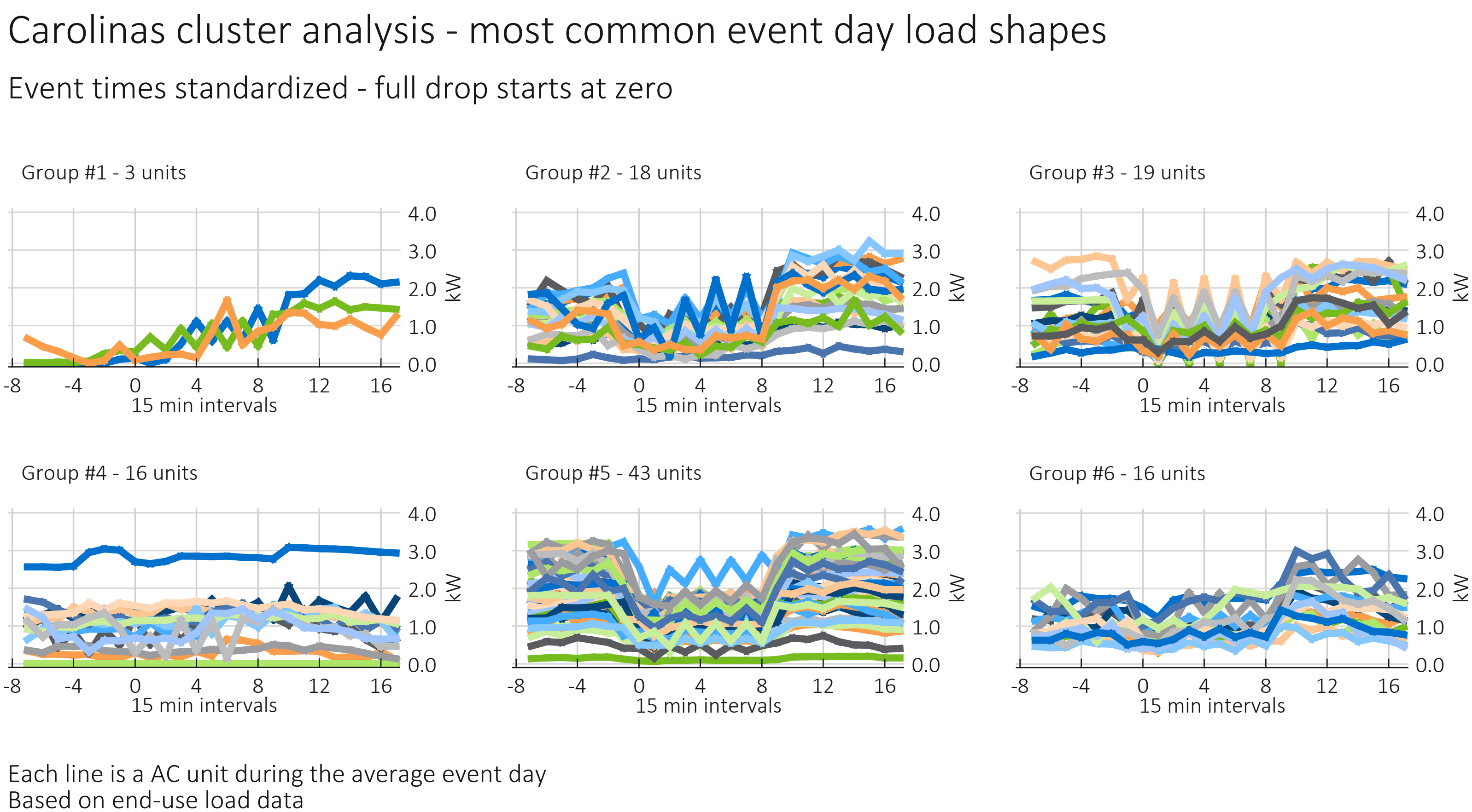



Figure 6-2 visualizes the categorization for individual units. The customers in each group follow the prototypical shapes but sometimes differ in size due to the fact that the algorithm isolated shapes. In total, 19 of 115 units analyzed (16.5%) did not exhibit a demand reduction pattern and another 13.9% were assigned to group 6, which delivered smaller percent load reductions. It is important to separate performance from weather sensitivity and customer size. Smaller customers may be underperformers due to the lack of air conditioners, and are less cost effective, even with a functional device. Thus, we recommend focusing direct verification efforts on larger customers.

Figure 6-2: Event Day Load Shape Clusters



## 6.3 Key Findings

Key findings from the investigation into device operability include:

- End use data loggers were only installed on air conditioner units with functional load control devices;
- Based on field tests, 144 out of the 154 (93.5%) devices tested are operable, with a 90% confidence interval of ±3.27%, excluding devices that do not perform due to paging network issues or because the air conditioner is not in use during afternoon peak hours of hotter days;
- Most sites with inoperable devices have multiple failures;
- The event day load profiles suggest that 19 of 115 units analyzed (16.5%) did not exhibit a demand reduction pattern. This could be due to failing or missing devices, paging network issues, or lack of air conditioner loads; and
- Efforts to inspect paging network strength and verify that devices are present and operable should focus on larger customers. They are less prone to misdiagnosis and more cost effective.

# 7 Process Evaluation

Process evaluation, particularly when combined with the insight obtained from impact evaluation, informs efforts to continuously improve programs by identifying program strengths and weaknesses, opportunities to improve program operations, program adjustments likely to increase overall effectiveness, and sources of satisfaction or dissatisfaction among participating customers. The primary objectives for the process evaluation component of the evaluation include:

- Assessing the extent to which participants are aware of events, bill credits, and other key program features;
- Understanding the participant experience during events: comfort, occupancy, thermostat adjustments, and strategies employed to mitigate heat;
- Identifying motivations and potential barriers for participation, including expectations, sources of confusion or concern, intention to stay enrolled, and likelihood of recommending the program to others;
- Documenting the operations, recruitment, enrollment, outreach, notification, and curtailment activities associated with program delivery; and
- Identifying program strengths and potential areas for improvement.

## 7.1 Survey Disposition

Nexant developed a survey for customers participating in the Power Manager program that was deployed immediately following a Power Manager event. The survey was administered via phone and email to maximize response rates during the 24 hour window directly following a Power Manager event. The post-event survey addressed the following topics:

- Awareness of the specific event day.
- Any actions that increased household comfort during a Power Manager event. Do participants report changing AC settings, using other equipment (including window units, portable units, or ceiling fans) to mitigate heat buildup? Were participants home during the event? Are they usually home during that time period?
- Satisfaction with the Power Manager program and bill credits earned.
- Expectations and motivations for enrolling. What did participants expect to gain from enrollment? To what extent are they motivated to earn incentive payments versus altruistic motivations such as helping to address electricity shortfalls during periods of high peak demand and/or reducing the environmental effects of energy production?
- Do participants expect to remain enrolled in the program in future years?

In addition to the post-event survey, a nonevent survey was also deployed immediately following a hot, nonevent day. This nonevent day survey was identical to the post-event survey to establish a baseline and facilitate comparison with the results of the event day survey. Both the event and nonevent surveys were administered to Power Manager participants. Since event awareness and thermal comfort are primary areas of inquiry for the survey, the nonevent baseline data (from the nonevent surveys) provides the opportunity to net out any propensity for thermal discomfort or belief that a Power Manager event is occurring that would naturally happen on any hot day of the summer. In this way, it is possible to evaluate whether statistically significant differences in event awareness and reports of thermal discomfort exist between customers who actually experience a Power Manager event and customers who do not.

The survey was completed by 95 customers on an event day (the *event* group) and 89 customers on a hot nonevent day (the *baseline* group). The overall response rate was 9%. All surveys were conducted on the day of the event or the nonevent. The plan was to survey about 50% of respondents by phone and 50% by email, but on the event day more people were reached by telephone than expected. The distribution of phone calls and emails, with response rates, is shown in Table 7-1 . All responses in this section summarizing survey results have been weighted to reflect the survey design for 50% of completions by phone and email each.

The temperature on the event day was a high of 94°F with a heat index of 95°F, which was nearly the same as the temperature on the nonevent day, which was a high of 95°F with a heat index of 95°F. Table 7-1 outlines the event and nonevent baseline group survey dispositions.

Table 7-1: Survey Disposition

| Total Responses | Group Size | Date | Temperature | Phone/ Email Distribution | Response Rate |
|---|---|---|---|---|---|
| 184 Responses | 95 Event Day | Thursday, September 8 | high 94° F (heat index 95° F) | 56% Phone | 13% |
| | | | | 44% Email | 6% |
| | 89 Nonevent day (Baseline) | Wednesday, July 13 | high 95° F (heat index 95° F) | 58% Phone | 16% |
| | | | | 42% Email | 6% |

Most households surveyed have two or fewer residents, and only 8% of event and 17% of nonevent baseline households have four or more residents. There was no apparent systematic difference in the age of respondents between the event and nonevent baseline groups. The mean age of respondents is 65 years and the most commonly reported level of education was a bachelor's degree: 29% of respondents said that they graduated from college. Nearly as many (26%) have some college or an associate's degree and 22% have a graduate or professional degree.

## 7.2 Program and Event Awareness

The customer surveys were designed with the key objective of evaluating participants' awareness of Power Manager events, but a few questions were also included to gauge participants' general awareness of the program and its key features. Every respondent who was contacted to complete the survey was a Power Manager participant at the time of the survey, and a strong majority of the respondents, 85%, reported that they are in fact familiar with the Power Manager program. Respondents also reported on whether or not they had seen Power Manager event credits on their bill. Less than a majority of respondents affirmed that they have seen credits on their bill: 32% of respondents reported that they have seen a credit, while 35% reported that they had not, and the balance of respondents, 33%, reported that they did not know. It is possible that due to the timing of the nonevent survey, which was midseason, these customers had not yet seen credits in 2016. With many customers receiving paperless bills, it is possible that some customers rarely look at the line item details on their monthly statement. Duke Energy screened the list of customers who said they did not receive bill credits to make sure errors were not made; all in fact received a bill credit when they should have.

Both of these questions were asked of both the event group and the nonevent baseline group. That is, the questions were asked of a group of customers that had experienced a Power Manager event that day and a group of customers who had not. It would not be expected that there would be significant differences in these questions addressing program awareness between these groups. Indeed, the responses to these two questions do not significantly differ across event and nonevent baseline groups.

The bill credits are designed to be a program feature that enhances customer satisfaction with the program; with less than half of respondents recalling receiving a bill credit, an opportunity exists to improve participants' awareness of this customer-friendly program feature.

Every Power Manager participant who was randomly selected to receive the post-event survey, i.e., the event group, experienced an actual Power Manager event that day, Thursday, September 8. A total of 95 customers completed the post-event survey. Only 12% of the event group respondents reported that their homes were uncomfortable that day, while all of them experienced a load control event that afternoon. As a program with no pre-event notification, a decrease in thermal comfort in the home is the key factor for assessing event awareness. In the Carolinas, with only 12% of respondents stating that they were uncomfortable the day of the event, event awareness by that measure is quite low. However, it could also be that a number of those respondents would say that their home was uncomfortably hot at times on any hot day of the year, regardless of whether or not the Power Manager program had a load control event. To control for this possibility, another randomly selected group of Power Manager participants were also surveyed on a hot day when a Power Manager event did not occur, Wednesday, July 13. A total of 13% of respondents reported that their home was uncomfortable on this nonevent day. The small difference in the portion of respondents in the post-event survey and the nonevent survey that stated that their homes were uncomfortable that day (12% and 13%, respectively), is not statistically significant, therefore, the increase in reported thermal discomfort cannot be ascribed to the Power Manager event. The response frequencies are tabulated in Table 7-2.

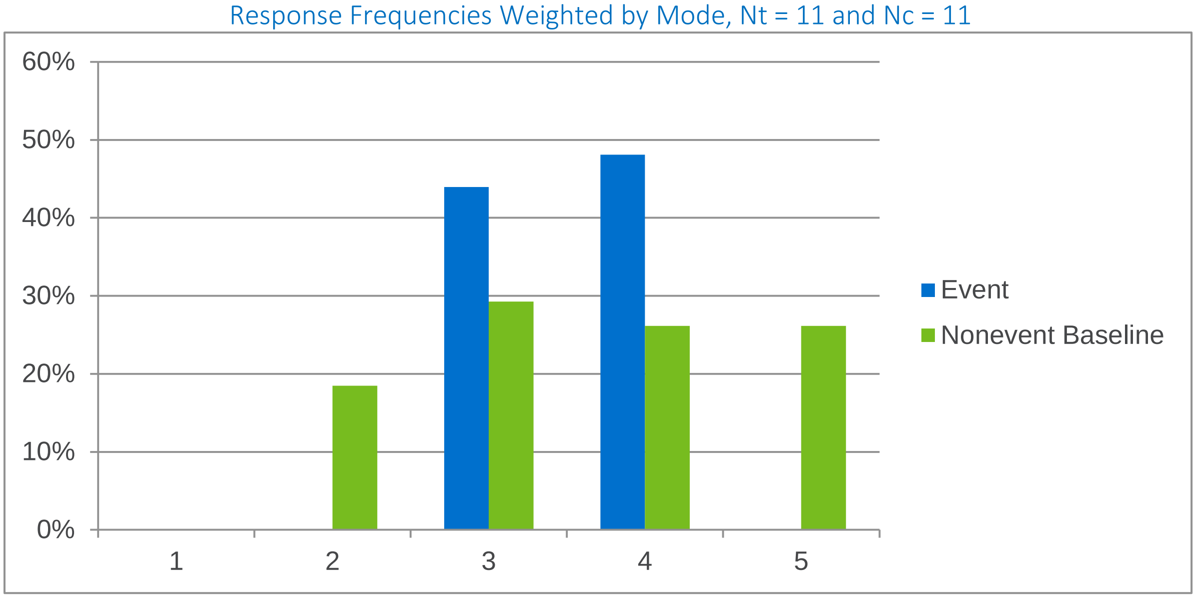
Table 7-2: Was there any time today when the temperature in your home was uncomfortable? Response Frequencies Weighted by Mode, Nt = 95 and Nc = 89

| Response | Event | Nonevent Baseline |
|---|---|---|
| Yes | 12% | 13% |
| No | 78% | 78% |
| Don't know | 9% | 9% |
| Refused | 1% | 0% |

Of those relatively few customers (11 post-event and 11 nonevent survey respondents) who reported that they were uncomfortable at some time during the day of the survey, the majority (12 people) reported becoming uncomfortable between 2 and 3pm. The rest were distributed throughout the day, from 4am to 6pm. Asked when the period of thermal discomfort in their home ended, there was a shift in responses towards later in the day, with 16 respondents reporting that their homes stopped feeling uncomfortable between 4 and 7pm. Three respondents listed times earlier than 4pm, and one respondent listed 10pm.

These customers who reported thermal discomfort were also asked to rate their discomfort using a five-point scale, where 1 represents "not at all uncomfortable" and 5 represents "very uncomfortable." Frequencies of the responses are summarized in Figure 7-1, for which the chi-squared statistical test shows no discernable difference in the distributions of post-event and nonevent survey responses (at the 90% level of confidence). In sum, there appears to be no difference in thermal discomfort between the event group and the nonevent baseline group. The survey does not present evidence that Power Manager events led to more customers reporting discomfort in their homes, or to higher degrees of discomfort.

Figure 7-1: Please rate your discomfort using a scale of one to five, where one means "not at all uncomfortable" and five means "very uncomfortable."
Response Frequencies Weighted by Mode, Nt = 11 and Nc = 11



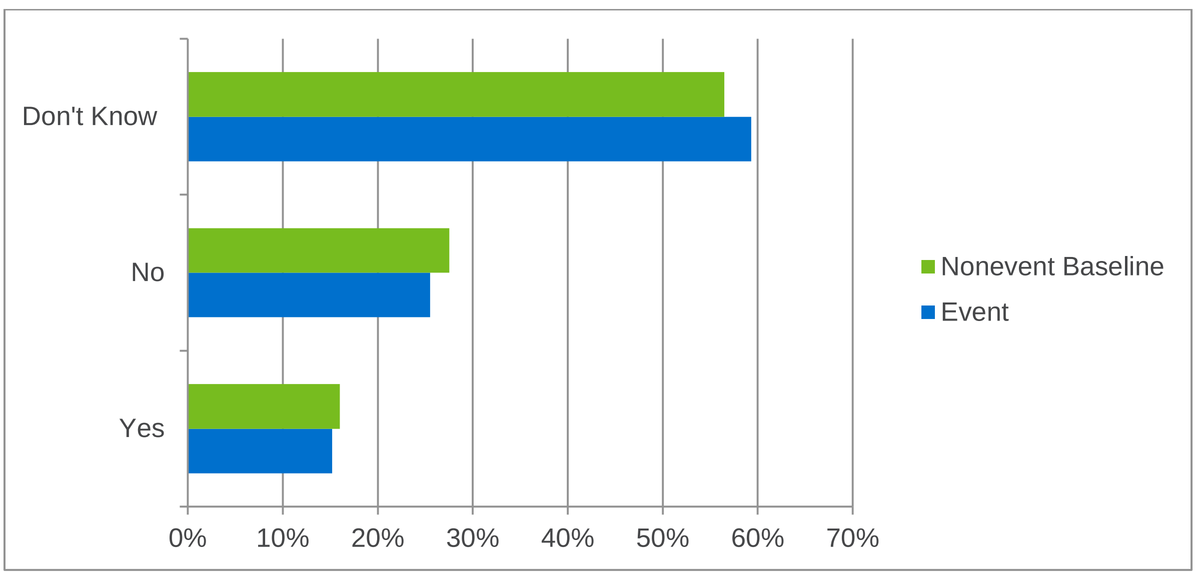

Those respondents who reported that their homes had been uncomfortably hot that day were asked to state in their own words what they think caused the discomfort. The most commonly reported rationale is that the discomfort in their home was due to the weather being hot; 54% of 11 event respondents and 26% of 11 nonevent respondents gave that reason. The second most common reason was that the air conditioner was not on: 30% of event and 15% of nonevent respondents said this. Only 16% of event respondents and 11% of nonevent respondents ascribed their thermal discomfort to Duke controlling their air conditioners (not a statistically significant difference). Table 6-3 summarizes the responses given to this survey question, across event and nonevent baseline customers and altogether. The totals may not add up to 100% because respondents could cite more than one reason. The difference in distribution of answers between the two groups is not statistically significant; this is not unexpected given the small number of customers who answered this question.

Table 7-3: What do you think caused the temperature to be uncomfortable?
Response Frequencies Weighted by Mode, $N_t = 11$ and $N_c = 11$

| Reason | Event | Nonevent Baseline | All |
|---|---|---|---|
| Air conditioner unit was not on | 30% | 15% | 23% |
| Air conditioner doesn't work properly | 0% | 22% | 11% |
| Duke Energy was controlling air conditioner | 16% | 11% | 13% |
| It was a very hot day | 54% | 26% | 40% |
| Other | 0% | 26% | 13% |

All survey respondents were also asked directly whether or not they thought a Power Manager event had been called in the past few days. The most common response was "don't know," where 59% of event customers and 56% of nonevent customers stated that they didn't know if there was a Power Manager event in the past few days. The prevalence of "don't know" responses here is not surprising in light of the fact that Duke Energy does not actively notify participants of load control events. Figure 7-2 presents response frequencies for event and nonevent respondents; the differences between event and nonevent responses to this question were not statistically significant. Across all respondents together, 58% did not know if there was a Power Manager event recently, 16% thought that there was an event recently, and 26% did not think that there was an event recently.

Figure 7-2: Do you think a Power Manager event occurred in the past few days?
Response Frequencies Weighted by Mode, $N_t = 95$ and $N_c = 89$




The relatively few respondents (14 event and 13 nonevent) who thought there was a Power Manager event recently were asked a few questions about the event(s) that they perceived to have happened. First, when asked on what day they thought the event occurred, 36% of the event customers correctly stated that there was an event that day; for comparison, 6% of nonevent customers said there was an event day that day. Directionally, these survey responses indicate that among customers who thought a Power Manager event recently occurred, customers who actually experienced an event that day are more likely to correctly identify that event day than customers who did not actually experience an event that day. But with only a single nonevent baseline customer and five event customers to compare in this response category, it is not possible to rule out that this difference is due to chance alone.

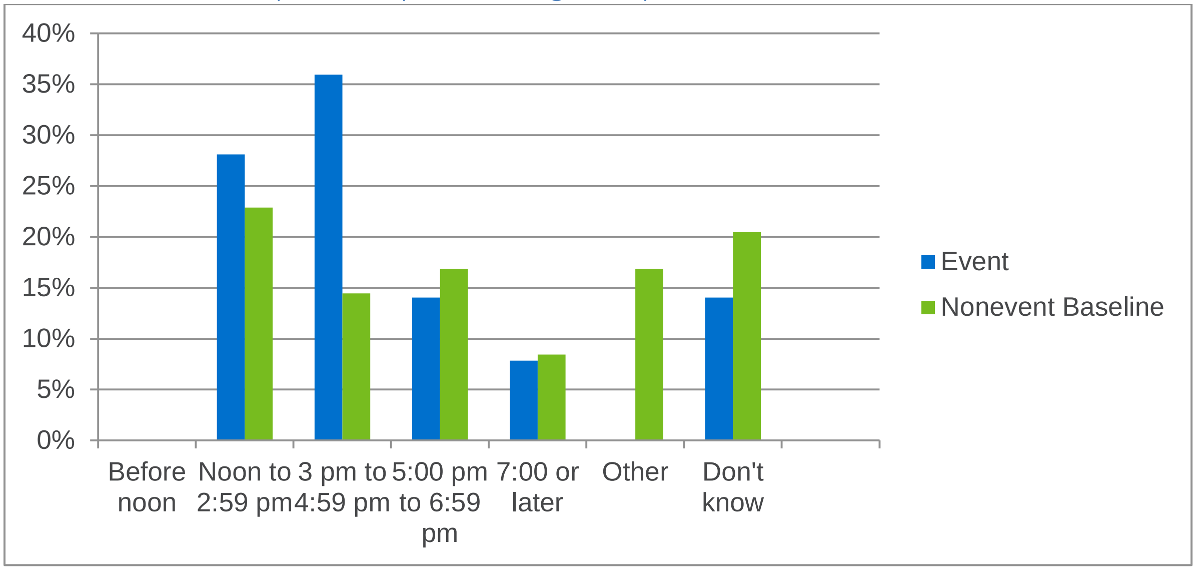
These customers were also asked to describe how they determined that a Power Manager event was occurring, and the responses are summarized in Table 7-4. The most common response, given by 57% of respondents, is that they concluded an event was occurring because the temperature inside their home went up. The next most commonly reported rationale was because they did not hear the air conditioning running the way they normally do, with 14% of respondents giving this reason. There were no statistically significant differences between the response patterns of event customers and nonevent customers for this question.

Table 7-4: How did you determine that an event was occurring?
Response Frequencies Weighted by Mode, $N_t$ = 14 and $N_c$ = 13

| Reason | Event | Nonevent Baseline | All |
|---|---|---|---|
| It got warmer inside - the inside temperature went up | 58% | 53% | 57% |
| Did not hear the air conditioner running like I knew it should | 14% | 14% | 14% |
| Some other way | 8% | 8% | 8% |
| It was a hot day outside - I knew from the temperature outside | 6% | 0% | 3% |
| Don't know | 8% | 22% | 15% |

These respondents who thought there was a Power Manager event recently were also asked what time they thought the event occurred and whether or not they were home at that time. All respondents said that they first noticed the event during the period of noon to 7pm, except for two who noticed it during the night and several who said they were not sure. However, the event customers tended to respond that they thought the event started earlier in the day, while the nonevent customers' responses resembles a uniform distribution across time of day. The chi-squared test for differences in these distributions is statistically significant at the 95% level of confidence (p-value = 0.028), suggesting that the event customers who noticed an event tended to notice it closer to the time it actually started and that nonevent customers were not any more likely to think that a perceived event began at any particular time of day, consistent with the fact that they did not actually experience an event.

Figure 7-3: About what time did you first notice this event?
Response Frequencies Weighted by Mode, $N_t$ = 14 and $N_c$ = 13




## 7.3 Program Experience

Aside from occasional program communications to program participants, the primary way that Duke Energy customers experience the Power Manager program is during load control events. A large majority of survey respondents, 83%, stated that there is normally someone home between the hours of noon to 6pm on weekdays. Similarly, large proportions of respondents also reported that they are frequent users of their air conditioning systems. Table 7-5 shows the percentage of respondents who reported that they used their air conditioners every day for four different time periods and day type combinations. Generally, between 85% and 94% of Power Manager survey respondents reported using their air conditioners every day, considering both weekdays and weekends, during both the afternoon and the evening. Statistically significant differences in response patterns were not observed here.

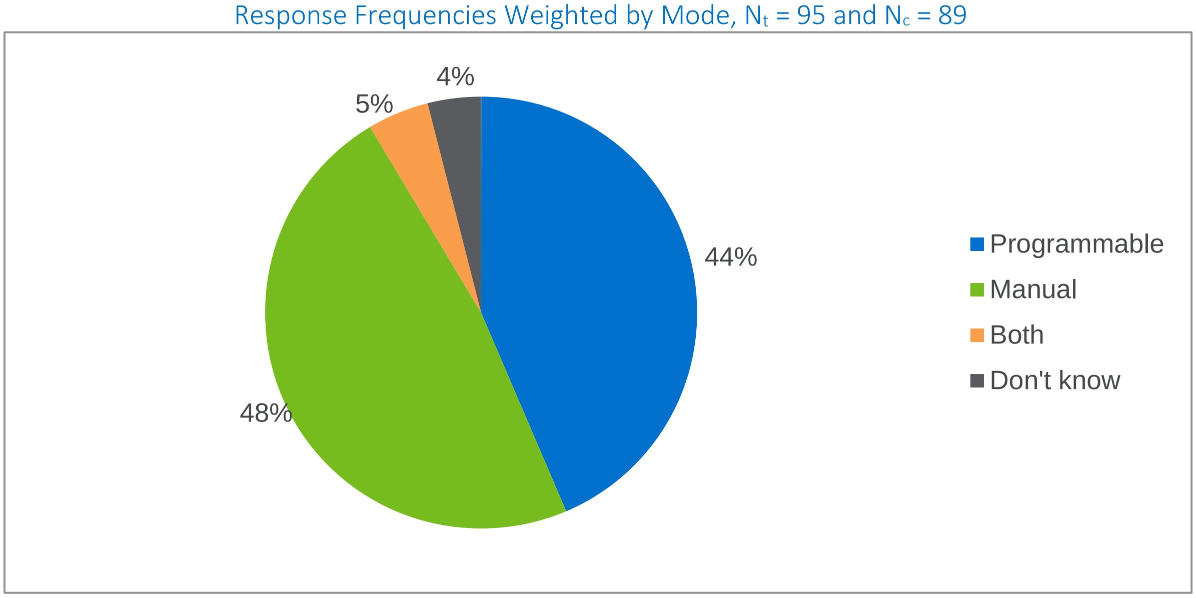
These survey responses confirm that Power Manager participants are in fact largely at home and using their air conditioners during the times that the program is likely to be launched when the need arises to use the program resource. As such, monitoring participant comfort levels is confirmed to be an important evaluation activity so that thermal comfort can be maintained at high enough levels to retain customer participation.

Table 7-5: How frequently do you or someone else in your household use your air conditioning system? Response Frequencies Weighted by Mode, $N_t$ = 95 and $N_c$ = 89

| Day and Time | % of Event Respondents Responding "every day" | % of Nonevent Respondents Responding "every day" |
|---|---|---|
| ...weekday afternoons (12-6 PM) | 85% | 94% |
| ...weekend afternoons (12-6 PM) | 90% | 94% |
| ...weekday evenings (6 PM-12 AM) | 87% | 89% |
| ...weekend evenings (6 PM-12 AM) | 90% | 94% |

In addition to occupancy patterns and frequency of air conditioning usage, Power Manager participants' experience with the program is affected by how they operate their air conditioning systems. Beginning with the type of thermostat(s) installed in the home, survey responses show that there is a mix of both manual and programmable thermostats installed in the homes of Power Manager participants. Figure 6-4 summarizes the types of thermostat(s) that survey respondents reported. About half, 48%, have a manual thermostat, while 44% of respondents say that they have a programmable thermostat.

Figure 7-4: What type of thermostat(s) do you have?
Response Frequencies Weighted by Mode, $N_t$ = 95 and $N_c$ = 89




Among the customers who have programmable thermostats, 32% reported using the programmability feature to allow the thermostat to cool to different temperatures at different times, and a further 58% of customers set their thermostat at a constant temperature, representing 90% of respondents. Among customers without programmable thermostats, 60% say that they keep their thermostat set at a constant temperature. This relatively high incidence of using a thermostat setpoint should encourage thermal comfort associated with events. If during the course of an event, the home's internal temperature rises by one or two degrees, when the event is over, the thermostat will reliably detect the higher temperature and automatically cool the home to the desired temperature, without relying on the customer to feel uncomfortable first and manually turn the air conditioning on themselves. These reported air conditioning usage behaviors are supportive of the earlier finding that, on the whole, Power Manager participants are not aware of events when they occur.

In a similar vein, we asked customers who reported that they thought there was a Power Manager event recently whether or not they took any actions as a result of the perceived event. Only 5 customers (of 27 who said that they thought there was a Power Manager event) said they did something different because of the event. They all reported using fans they do not normally use, but none of them used any extra air conditioning units. None of them left home to go somewhere cooler, and only one customer reported changing their planned activities. Responses to these questions also provide more evidence that Power Manager events are not disruptive to participants. Participants who used other appliances for cooling chose fans, a low-energy usage cooling appliance.

## 7.4 Motivation and Potential Barriers for Program Participation

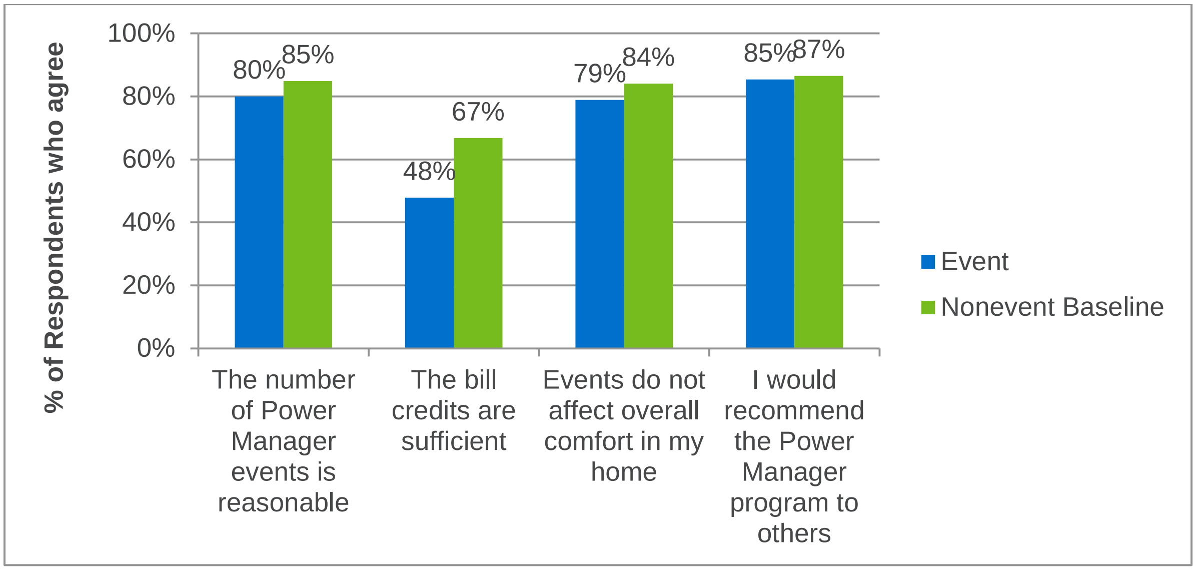
Respondents were provided with a list of possible reasons for enrolling and asked which reason was most important to them, and the survey responses reveal that Power Manager participants are motivated to be a part of the program by a diverse set of interests. The most frequently reported motivation is the bill credits, with 49% of respondents citing this as their most important motivator. The second-highest motivator is helping the environment; 17% of respondents said helping the environment was the most important reason for enrolling. The remaining 34% of respondents were mostly split between "doing my part for DEC" and "avoiding electrical service interruptions." Only 8% answered "don't know." Table 7-6 summarizes the survey responses. Differences in response patterns between event and nonevent baseline groups are not statistically significant.

Table 7-6: Which of the following reasons was most important to you when enrolling?
Response Frequencies Weighted by Mode, $N_t$ = 95 and $N_c$ = 89

| Reason | Event | Nonevent Baseline | All |
|---|---|---|---|
| Earning a credit on my bill | 53% | 44% | 49% |
| Helping the environment | 13% | 20% | 17% |
| Doing my part for DEC | 12% | 16% | 14% |
| Avoiding electrical service interruptions | 8% | 16% | 12% |
| Don't know | 13% | 4% | 8% |

Customers were asked to rate, on a scale of 1 to 5, their agreement with various positive statements about Power Manager. Customers widely agreed that they would recommend the Power Manager program to others; that Power Manager events do not affect the overall comfort in their home; and that the number of Power Manager events is reasonable. Over 75% of both event and nonevent baseline customers agreed with those statements. But only 67% of event customers and 48% of nonevent baseline customers agree that the bill credits are sufficient. The distribution of responses for those who answered each question is shown in Figure 7-5.

Figure 7-5: How would you rate the following statements about Power Manager?
Response Frequencies Weighted by Mode, $N_t$ = 95 and $N_c$ = 89




The survey concluded with an opportunity for customers to provide free form suggestions on how they think the Power Manager program might be improved. Only 34% of respondents (62 of 184) offered suggestions. Among those offering suggestions for improvement, there were four common requests. The first, mentioned by 20 of 62 people, reflected a desire for more bill credits. The second, mentioned by 13 people, expressed a desire for notification before or during an event:

- "Maybe develop a better way to advise customers when the system is being activated, as well as the reasons for activation."
- "It would be nice if Duke would call and let me know when they're going to turn it off."
- "Since you have my email, we could be notified when you activate the program."
- "Provide a text message advising it is/will happen."

The third most common comment, reported by 10 people, was that Power Manager is a good program. Several commented that the program is imperceptible to them, and some commented that the program is flawless except for the small bill credits:

- "I don't ever notice it, so it works fine for me."
- "It's invisible."
- "They got a good thing going."
- "If they could lower our bills. Otherwise, I give them a good rating."
- "It's a good program…I do think that possibly the program could be adjusted $$-wise."

Five people complained about the load control and suggested that Duke change the cycling pattern. Many of these comments are based on flawed understanding of the program. Six people mentioned that they would like to have feedback after an event to inform them about their participation and the credits they earned; sometimes they don't read their bill closely and they want a more prominent notification. Some of the comments in these areas include:

- "After an event when the power comes back on it needs to stay on for at least 20 minutes or so. In the past it came on then went right back off in 5 minutes then went off for the normal off time then came back on and went off in 5 minutes."
- "My bill comes directly to online banking, so I don't actually look at a statement anymore. I'm on EPP, so I don't see the credits. Could you send an email when you issue a credit, so I know I'm getting the benefit?"

Table 7-7 summarizes categorizations of the freeform responses. Many respondents gave more than one comment, and often they gave one comment that fit into a specific category and one that fell into "other." Since the answers often fit into multiple categories, the percentages add up to more than 100%.

Table 7-7: What suggestions do you have to make the Power Manager program work better for you? Response Frequencies Weighted by Mode, $N_t$ = 34 and $N_c$ = 28

| Statement | Event | Nonevent Baseline | All |
|---|---|---|---|
| I want more credits | 30% | 35% | 32% |
| Other | 31% | 16% | 24% |
| I want more notification | 30% | 12% | 21% |
| It's a good program | 15% | 18% | 16% |
| I want more feedback | 9% | 12% | 10% |
| Change the cycling strategy | 11% | 4% | 8% |

Responses were positive when participants were asked to rate the likelihood of staying enrolled in Power Manager, with the large majority of respondents saying that they intend to stay in the program. Overall, 78% of respondents said they would "very likely" remain enrolled. Responses are tabulated in Table 7-8. The four customers who said they were not at all likely to stay enrolled gave disparate explanations. Their explanations are shown in Table 7-9.

Table 7-8: How likely is it that you will stay enrolled in Power Manager? Would you say…? Response Frequencies Weighted by Mode, $N_t$ = 95 and $N_c$ = 89

| Response | Event | Nonevent Baseline | All |
|---|---|---|---|
| Not at all likely | 4% | 0% | 2% |
| Somewhat likely | 11% | 14% | 12% |
| Very likely | 79% | 77% | 78% |
| Don't know | 5% | 8% | 7% |

Table 7-9: Why are you not at all likely to stay enrolled in Power Manager?
$N_t$ = 4 and $N_c$ = 0

| Response | Group |
|---|---|
| I am now home all the time due to a disability. | Event |
| I do not want this program. I am not supposed to be in this program. | Event |
| It is very uncomfortable. | Event |
| They have not been truthful about the program; they don't save me money. | Event |

## 7.5 Interview Findings

Power Manager is a mature demand-side resource that is actively used in the course of operating Duke Energy Carolinas' electric system. The demand savings delivered by Power Manager are made possible through the teamwork of internal and external stakeholders that manage the program's budget and goals, communicate with participants, maintain the Yukon event dispatch software, and interact with the customer at every stage of the program lifecycle, from enrollment, to device installation, to device removal. Three primary stakeholder groups, the Duke Energy program management team, Eaton Power Systems, and GoodCents, worked together to deliver Power Manager to customers. Nexant interviewed seven individuals from these organizations. Overall, through the course of our conversations, we observe that Power Manager maintains a customer focused orientation and is currently engaged in a number of initiatives to improve program operations and customer service. The remainder of this section will describe the Power Manager offering at DEC and what Duke Energy's activities are to bring in new program participants and support annual enrollment goals. A description of Duke Energy's activities to maintain Power Manager as a reliable system resource follows, which is followed in turn by an outline of work that continues after each load control season concludes to ensure Power Manager's continued success. This section concludes with a review of the activities that are planned or currently underway to further improve program operations and participating customer experience.

### 7.5.1 Program Offer and Enrollment Goals

Work to recruit new Duke Energy Carolinas participants into Power Manager takes place year-round. DEC's enrollment goal for 2016 was 19,750 devices. This relatively high annual enrollment target requires a year-round recruitment effort, rather than a shorter campaign limited to the spring season. The majority of recruitment into Power Manager takes place through outbound calling, fulfilled by the third party call center provider, CustomerLink. In some years, there are also direct mail and email recruitment campaigns initiated and managed by Duke Energy.

As an outbound call center, CustomerLink is prepared to address common questions or concerns that DEC customers who are not familiar with the program may have, in addition to describing the basic features of the program, many of which are friendly to the program participants. Outbound callers are ready to speak to the fact that Duke Energy's customer research has shown that 85% of customers who are home during an event don't notice it, that there are generally only five to seven events each summer, and that events typically end by 6pm, which is when many customers are just coming home from work. Another participant friendly aspect of the program is that air conditioning units enrolled in the program are cycled rather than completely curtailed.[8] Power Manager is also not called on weekends or weekday holidays. The load control devices used by the program—switches that directly control the air conditioner's compressor—are a proven technology that does no harm to the customer's air conditioner or the home's electric distribution system. Figure 6-6 provides an example of recent Power Manager marketing collateral used in the DEC jurisdiction.

Figure 7-6: Excerpt from Power Manager Direct Mail Marketing Collateral


The Duke Energy Carolinas program offer provides monthly bill credits in the amount of $8 to incentivize participation, where the bill credits apply from July to October. With only a modest financial incentive

---

8 Unless a load control event is called as a result of a system emergency. In that case air conditioning units could experience full load shed. Emergency Power Manager events are extremely rare.

for participation, Duke Energy emphasizes messaging around community and environmental benefits to generate customer interest in the program. The program offer, which centers on the use of the outdoor switch, rather than an indoor programmable communicating thermostat, is found generally to be most successful with customer segments that are attracted to “set-it-and-forget-it” arrangements and those customers who would prefer not to have a service provider enter the home. Duke Energy has found that these preferences are correlated with older, higher income, and higher education demographics.

GoodCents is a third party provider that manages Power Manager customer care and handles participants’ inquiries about the programs and requests for customer service, in addition to all fieldwork. Power Manager fieldwork ranges from scheduling and routing load control device installations, training and managing a staff of device installers, responding to any device service calls, and fulfilling customer requests to remove load control devices. GoodCents reports that most new device installations are handled within 30 days of the customer’s enrollment, and that most customers don’t request installation appointments to work around pets or access issues. As a result, most installation appointments can be fulfilled using cost-effective routing and scheduling. GoodCents also manages and staffs all quality assurance inspections and fieldwork.

### 7.5.2 Power Manager Program Operation and Maintenance

In terms of maintaining Power Manager as a reliable system resource for the Duke Energy Carolinas system operators, Eaton Power System plays an important role as the provider of the switches and as a resource to assist Duke Energy program staff in maintaining the Yukon software system, managing firmware issues that can arise from time to time, addressing the switches for normal service and evaluation, measurement and verification (EM&V) activities and training GoodCents’ switch installers. An annual all-hands Spring Training event hosted by Duke Energy brings all the Power Manager program stakeholders together to discuss the upcoming load control season’s work. Also particular to 2016, a large scale quality assurance audit effort of load control switches was undertaken and staffed by GoodCents.

When it’s time to start calling events during the summer load control season, there is no proactive customer notification for each event. However, customers may call a toll-free number to get updates on the status of whether or not Duke Energy plans to call or has called a Power Manager event. At Duke Energy Carolinas, program managers decide when load control events will be called on a day-of basis, mainly considering local system and weather conditions. The DEC System Operations Center (SOC) also has access to dispatch Power Manager on an emergency basis; however, Power Manager has very rarely been used in this emergency capacity. Under normal operations, the event calling team involves staff in SOC and Fuel and Systems Optimization in addition to demand response operations. However, overall demand response operations staff maintain control of the decision to call nonemergency events. Power Manager is viewed as an important resource for the Duke Energy Carolinas system that depends on the participating customers’ willingness to remain enrolled. Therefore, all events are called with a view towards whether or not it will be a detriment to the experience of the participants. Considerations taken in this area are the number of events that have already been called during the current summer, or, during heat spells, during that week. Demand response operations staff also consider other finer points that lie outside of the program rules that can influence customers’ willingness to continue to participate in the program; for example, whether or not Power Manager event hours have frequently gone into the late afternoon/early evening.

### 7.5.3 Program Monitoring and Postseason Program Maintenance

Duke Energy undertakes a number of activities both during the load control season and afterward to ensure that participants are satisfied with their Power Manager program experience and that the program is on track to provide an excellent customer experience going forward.

GoodCents, as the third party contractor that manages Power Manager customer contacts, has service level agreements in place with Duke Energy that outline service benchmarks, with both penalties for nonperformance and opportunities for incentives when benchmarks are exceeded. There are specific benchmarks in place to ensure that, during event days in particular, customer calls coming into GoodCents are handled quickly, efficiently, and that accurate information is provided to the customers calling in. Additionally, Duke Energy program managers monitor the number of calls coming in to the toll-free notification line, in addition to the number of calls coming into the GoodCents call center to detect any emerging issues associated with the program experience. Device removal requests are also tracked for this purpose.

Duke Energy uses seasonal reminder/thank you cards that are sent near the start of the load control season to: remind and thank customers for their participation in the program, provide tips for having a comfortable experience with the program, and recognize the program's contributions to reducing system load.

### 7.5.4 Upcoming Program Changes and Initiatives

Duke Energy is also engaged in initiatives to change the program offering to make it more attractive to customers and to improve program performance. Duke Energy Carolinas will be assessing using its website as an additional source of event notification, making it easier for customers to access information about Power Manager events. Finally, Duke Energy is also engaged in replacing certain models of older switches.

## 7.6 Key Findings

Key findings from the process evaluation include:

- 95 Power Manager participants were surveyed within 24 hours of the September 9 event, which had a high temperature of 94°F with a heat index of 95°F.
- 89 Power Manager participants were interviewed during a hot nonevent day, July 13, which had a high of 95°F with a heat index of 95°F. The nonevent day survey was used to establish a baseline for comfort, event awareness, and other key metrics.
- A strong majority of all respondents, 85%, reported that they are familiar with the Power Manager program.
- Only 12% of respondents on the event day reported that their homes were uncomfortable, while all of them experienced a load control event that afternoon. By comparison, 13% of Power Manager customers surveyed on a hot nonevent day reported they felt uncomfortably hot. This

small difference is not statistically significant—we cannot conclude that there is a difference in customers' thermal discomfort due to Power Manager events.

- More than 85% of participants would recommend the Power Manager program to others.
- The Power Manager staff and vendors are customer focused and undertake a number of activities both during the load control season and afterward to ensure that participants are satisfied with their Power Manager program experience.

# Appendix A Regression Models Tested

All regression models were performed and the average customer loads throughout the summer using 15 minute interval data. The same sample of customers was analyzed using whole house interval and air conditioner end use data. The analysis only included days when maximum temperature exceeded 75˚F.

For the individual event day impacts (ex post), the regression equation took the general form of Equation 1, which will be estimated using a dataset made up of hourly observations of the average load in the M&V sample. Equation 2 describes the model used to estimate average event impacts for the general population events. The average event impacts were estimated separately to account for the effect of repeated events on confidence intervals.

Equation 1 and Equation 2 represent a within-subjects approach in which the observations on nonevent days are used to predict the counterfactual load for Power Manager customers on event days. A few points are noteworthy. The models were run separately for each 15 minute interval (equivalent to a fully interacted model) to account for occupancy patterns and produce different weather coefficients and constants. The only component that varied across the 10 models tested was how the weather variables were specified. Table A-1 shows the weather variables and explains the underlying concept for each model tested. To improve precision, same-day loads for the pre-event hours of 11am to 1pm were included to capture any differences between event and nonevent days that are not reflected in the model. The pre-event same day load variable functions as a same-day adjustment and is included because customers are not notified of the event in advance.

Equation 1: Ex Post Regression Model Individual Events

$$kW_{t,i} = a_i + \sum_{j=1}^{J} b_{i,j}\mathrm{event}_{t,j} + c \cdot preeventkW_t + d_i \cdot weather_{i,t} + \sum_{k=1}^{7} e_{i,k}\mathrm{dayofweek}_{i,k} + \sum_{l=5}^{10} f_{i,l}\, month_t + \varepsilon_{i,t}$$

Equation 2: Ex Post Regression Model Average Event (General Population Events)

$$kW_{t,i} = a_i + b_i\mathrm{avgevent}_t + c \cdot preeventkW_t + d_i \cdot weather_{i,t} + \sum_{k=1}^{7} b_{i,k}\mathrm{dayofweek}_{i,k} + \sum_{l=5}^{10} f_{i,l}\, month_t + \varepsilon_{i,t}$$

Where:

| | |
|---|---|
| $a$ | Is the constant or intercept |
| $b_{i,j}$ | Represents the event effect of Power Manager during each interval, $i$, and each event day, $j$ |
| $c$-$f$ | Are other model coefficients |
| $i$, $k$, $l$ | $i$, $k$ and $l$ are indicators that represent individual 15 minute intervals (96 in a day), days of the week, and months of the year |
| $t$ | Represents each date in the analysis dataset |
| $event$ | Is a binary variable indicating whether Power Manager was dispatched on that day |
| $preeventKW$ | Represents the same-day loads for the pre-event hours of 11am to 1pm. The variable functions as a same-day adjustment and is included because customers are not notified of the event in advance |
| $weather$ | 10 different ways to specify if weather was tested. Those are detailed in Table A-1 |
| $dayofweek$ | Are a set of mutually exclusive binary variables to capture day of week effects |
| $month$ | Are a set of mutually exclusive binary variables to capture monthly or seasonal effects |
| $\varepsilon$ | Represents the error term |

Table A-1: Weather Variables by Model Tested

| Model | Weather variables | Concept |
|---|---|---|
| 1 | Cooling Degree Hour Base 70˚F (CDH) | The same hour temperature drives electricity use but air conditioner loads are only linear when temperatures are above 70˚F |
| 2 | Cooling Degree Day Base 65˚F (CDD) | The overall daily average temperature drives electricity use but air conditioner loads are only linear when average daily temperatures exceed 65˚F |
| 3 | Daily Maximum Temperature | The daily maximum temperature drives air conditioner electricity use |
| 4 | Average temperature over the 24 hours immediately prior | Heat buildup over the 24 hours immediately prior to time period drives electricity use |
| 5 | CDH and CDD | Both the daily average temperatures and same hour temperatures drive air conditioner electricity use |
| 6 | Same hour CDH and average temperature over the 24 hours immediately prior | Air conditioner use if influenced both by the temperature during that hour and by average temperature over the 24 hours immediately prior |
| 7 | Same hour CDH and average CDH over the 6 hours immediately prior | Air conditioner use if influenced both by the temperature during that hour and by heat buildup, as measured by CDH, over the 6 hours immediately prior |
| 8 | Same hour CDH and average CDH over the 12 hours immediately prior | Air conditioner use if influenced both by the temperature during that hour and by heat buildup, as measured by CDH, over the 12 hours immediately prior |
| 9 | Same hour CDH and average CDH over the 18 hours immediately prior | Air conditioner use if influenced both by the temperature during that hour and by heat buildup, as measured by CDH, over the 18 hours immediately prior |
| 10 | Same hour CDH and average CDH over the 24 hours immediately prior | Air conditioner use if influenced both by the temperature during that hour and by heat buildup, as measured by CDH, over the 24 hours immediately prior |

# Appendix B Per Device Demand Reduction Tables

Table B-1: One Hour Event Per Device Demand Impacts by Cycling Strategy, Temperature, and Event Start

| True Cycle | Daily Max (F) | Start Time (1 Hour Event)* | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 12 PM | 1 PM | 2 PM | 3 PM | 4 PM | 5 PM | 6 PM |
| 50 | 74 | -0.06 | -0.08 | -0.10 | -0.10 | -0.11 | -0.12 | -0.11 |
| | 76 | -0.08 | -0.10 | -0.14 | -0.15 | -0.17 | -0.17 | -0.15 |
| | 78 | -0.08 | -0.11 | -0.15 | -0.17 | -0.18 | -0.19 | -0.17 |
| | 80 | -0.10 | -0.15 | -0.19 | -0.22 | -0.24 | -0.24 | -0.22 |
| | 82 | -0.13 | -0.18 | -0.24 | -0.28 | -0.31 | -0.31 | -0.29 |
| | 84 | -0.17 | -0.23 | -0.30 | -0.34 | -0.36 | -0.36 | -0.33 |
| | 86 | -0.22 | -0.29 | -0.36 | -0.41 | -0.43 | -0.43 | -0.39 |
| | 88 | -0.27 | -0.36 | -0.43 | -0.47 | -0.50 | -0.49 | -0.46 |
| | 90 | -0.31 | -0.41 | -0.49 | -0.53 | -0.56 | -0.55 | -0.50 |
| | 92 | -0.37 | -0.49 | -0.57 | -0.61 | -0.63 | -0.61 | -0.55 |
| | 94 | -0.41 | -0.53 | -0.62 | -0.66 | -0.69 | -0.67 | -0.62 |
| | 96 | -0.47 | -0.61 | -0.69 | -0.75 | -0.77 | -0.76 | -0.70 |
| | 98 | -0.49 | -0.65 | -0.75 | -0.80 | -0.83 | -0.82 | -0.75 |
| | 100 | -0.56 | -0.73 | -0.83 | -0.91 | -0.94 | -0.93 | -0.83 |
| | 102 | -0.55 | -0.73 | -0.82 | -0.91 | -0.97 | -0.96 | -0.90 |
| 64 | 74 | -0.06 | -0.07 | -0.08 | -0.09 | -0.09 | -0.10 | -0.10 |
| | 76 | -0.08 | -0.10 | -0.13 | -0.14 | -0.15 | -0.15 | -0.14 |
| | 78 | -0.08 | -0.10 | -0.13 | -0.15 | -0.16 | -0.16 | -0.15 |
| | 80 | -0.12 | -0.15 | -0.18 | -0.20 | -0.21 | -0.22 | -0.20 |
| | 82 | -0.15 | -0.19 | -0.23 | -0.26 | -0.27 | -0.28 | -0.26 |
| | 84 | -0.21 | -0.26 | -0.31 | -0.33 | -0.35 | -0.35 | -0.33 |
| | 86 | -0.28 | -0.35 | -0.40 | -0.43 | -0.45 | -0.45 | -0.42 |
| | 88 | -0.38 | -0.46 | -0.51 | -0.54 | -0.56 | -0.56 | -0.53 |
| | 90 | -0.45 | -0.54 | -0.60 | -0.63 | -0.65 | -0.64 | -0.61 |
| | 92 | -0.57 | -0.67 | -0.73 | -0.76 | -0.78 | -0.76 | -0.72 |
| | 94 | -0.68 | -0.79 | -0.86 | -0.90 | -0.91 | -0.90 | -0.86 |
| | 96 | -0.82 | -0.94 | -1.02 | -1.06 | -1.08 | -1.07 | -1.02 |
| | 98 | -0.89 | -1.03 | -1.11 | -1.16 | -1.18 | -1.17 | -1.12 |
| | 100 | -1.10 | -1.27 | -1.36 | -1.42 | -1.45 | -1.43 | -1.36 |
| | 102 | -1.13 | -1.31 | -1.39 | -1.46 | -1.51 | -1.50 | -1.45 |
| 100 | 74 | -0.16 | -0.20 | -0.25 | -0.26 | -0.28 | -0.30 | -0.28 |
| | 76 | -0.21 | -0.27 | -0.34 | -0.37 | -0.40 | -0.41 | -0.38 |
| | 78 | -0.22 | -0.28 | -0.37 | -0.41 | -0.44 | -0.46 | -0.42 |
| | 80 | -0.28 | -0.37 | -0.47 | -0.52 | -0.55 | -0.56 | -0.53 |
| | 82 | -0.34 | -0.45 | -0.57 | -0.63 | -0.68 | -0.69 | -0.65 |
| | 84 | -0.45 | -0.58 | -0.69 | -0.75 | -0.80 | -0.80 | -0.74 |
| | 86 | -0.56 | -0.71 | -0.82 | -0.89 | -0.93 | -0.93 | -0.87 |
| | 88 | -0.69 | -0.84 | -0.96 | -1.02 | -1.06 | -1.05 | -0.99 |
| | 90 | -0.77 | -0.94 | -1.06 | -1.13 | -1.17 | -1.15 | -1.08 |
| | 92 | -0.91 | -1.09 | -1.21 | -1.27 | -1.29 | -1.26 | -1.18 |
| | 94 | -1.01 | -1.19 | -1.31 | -1.37 | -1.40 | -1.38 | -1.31 |
| | 96 | -1.14 | -1.33 | -1.45 | -1.51 | -1.54 | -1.53 | -1.45 |
| | 98 | -1.19 | -1.41 | -1.53 | -1.60 | -1.64 | -1.62 | -1.53 |
| | 100 | -1.34 | -1.57 | -1.70 | -1.79 | -1.83 | -1.81 | -1.70 |
| | 102 | -1.35 | -1.59 | -1.69 | -1.80 | -1.87 | -1.86 | -1.79 |

*Estimates exclude 30 minute phase in period and reflect the average reduction expected for the event

Table B-2: 2 Hour Event Per Device Demand Impacts by Cycling Strategy, Temperature, and Event Start

| True Cycle | Daily Max (F) | Start Time (2 Hour Event)* | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 12 PM | 1 PM | 2 PM | 3 PM | 4 PM | 5 PM | 6 PM |
| 50 | 74 | -0.06 | -0.08 | -0.10 | -0.10 | -0.11 | -0.11 | -0.10 |
| | 76 | -0.09 | -0.11 | -0.14 | -0.15 | -0.16 | -0.16 | -0.14 |
| | 78 | -0.09 | -0.12 | -0.15 | -0.17 | -0.18 | -0.18 | -0.16 |
| | 80 | -0.12 | -0.16 | -0.20 | -0.22 | -0.23 | -0.23 | -0.20 |
| | 82 | -0.15 | -0.20 | -0.25 | -0.28 | -0.30 | -0.29 | -0.25 |
| | 84 | -0.19 | -0.26 | -0.31 | -0.34 | -0.35 | -0.34 | -0.29 |
| | 86 | -0.24 | -0.32 | -0.37 | -0.40 | -0.42 | -0.40 | -0.35 |
| | 88 | -0.30 | -0.38 | -0.44 | -0.47 | -0.48 | -0.46 | -0.40 |
| | 90 | -0.34 | -0.43 | -0.49 | -0.53 | -0.54 | -0.51 | -0.45 |
| | 92 | -0.41 | -0.51 | -0.57 | -0.60 | -0.60 | -0.56 | -0.49 |
| | 94 | -0.45 | -0.55 | -0.62 | -0.65 | -0.66 | -0.62 | -0.55 |
| | 96 | -0.52 | -0.63 | -0.70 | -0.74 | -0.74 | -0.71 | -0.62 |
| | 98 | -0.55 | -0.67 | -0.75 | -0.79 | -0.80 | -0.76 | -0.67 |
| | 100 | -0.62 | -0.75 | -0.84 | -0.90 | -0.91 | -0.85 | -0.74 |
| | 102 | -0.62 | -0.75 | -0.83 | -0.91 | -0.93 | -0.90 | -0.80 |
| 64 | 74 | -0.06 | -0.08 | -0.08 | -0.09 | -0.10 | -0.10 | -0.09 |
| | 76 | -0.09 | -0.11 | -0.13 | -0.14 | -0.15 | -0.14 | -0.13 |
| | 78 | -0.09 | -0.12 | -0.14 | -0.15 | -0.16 | -0.15 | -0.14 |
| | 80 | -0.13 | -0.16 | -0.19 | -0.20 | -0.21 | -0.21 | -0.19 |
| | 82 | -0.16 | -0.21 | -0.24 | -0.26 | -0.27 | -0.26 | -0.24 |
| | 84 | -0.23 | -0.28 | -0.31 | -0.33 | -0.34 | -0.33 | -0.30 |
| | 86 | -0.31 | -0.37 | -0.41 | -0.43 | -0.44 | -0.43 | -0.39 |
| | 88 | -0.41 | -0.48 | -0.52 | -0.54 | -0.55 | -0.54 | -0.50 |
| | 90 | -0.49 | -0.56 | -0.61 | -0.63 | -0.64 | -0.62 | -0.57 |
| | 92 | -0.61 | -0.69 | -0.74 | -0.76 | -0.76 | -0.73 | -0.67 |
| | 94 | -0.73 | -0.82 | -0.87 | -0.89 | -0.90 | -0.87 | -0.82 |
| | 96 | -0.87 | -0.97 | -1.02 | -1.05 | -1.06 | -1.03 | -0.96 |
| | 98 | -0.95 | -1.06 | -1.12 | -1.15 | -1.16 | -1.13 | -1.06 |
| | 100 | -1.17 | -1.30 | -1.37 | -1.42 | -1.42 | -1.38 | -1.28 |
| | 102 | -1.21 | -1.33 | -1.41 | -1.47 | -1.49 | -1.46 | -1.38 |
| 100 | 74 | -0.18 | -0.23 | -0.25 | -0.27 | -0.29 | -0.29 | -0.27 |
| | 76 | -0.24 | -0.30 | -0.36 | -0.39 | -0.41 | -0.40 | -0.36 |
| | 78 | -0.25 | -0.32 | -0.39 | -0.43 | -0.45 | -0.44 | -0.40 |
| | 80 | -0.33 | -0.42 | -0.49 | -0.54 | -0.56 | -0.55 | -0.50 |
| | 82 | -0.40 | -0.51 | -0.60 | -0.66 | -0.69 | -0.67 | -0.61 |
| | 84 | -0.51 | -0.63 | -0.72 | -0.77 | -0.80 | -0.77 | -0.70 |
| | 86 | -0.63 | -0.76 | -0.86 | -0.91 | -0.93 | -0.90 | -0.82 |
| | 88 | -0.77 | -0.90 | -0.99 | -1.04 | -1.05 | -1.02 | -0.94 |
| | 90 | -0.86 | -1.00 | -1.10 | -1.15 | -1.16 | -1.12 | -1.02 |
| | 92 | -1.00 | -1.15 | -1.24 | -1.28 | -1.28 | -1.22 | -1.12 |
| | 94 | -1.10 | -1.25 | -1.34 | -1.39 | -1.39 | -1.35 | -1.25 |
| | 96 | -1.23 | -1.39 | -1.48 | -1.53 | -1.54 | -1.49 | -1.38 |
| | 98 | -1.30 | -1.47 | -1.57 | -1.62 | -1.63 | -1.58 | -1.46 |
| | 100 | -1.46 | -1.63 | -1.74 | -1.81 | -1.82 | -1.75 | -1.61 |
| | 102 | -1.47 | -1.64 | -1.75 | -1.83 | -1.86 | -1.82 | -1.70 |

*Estimates exclude 30 minute phase in period and reflect the average reduction expected for the event

Table B-3: Three Hour Event Per Device Demand Impacts by Cycling Strategy, Temperature, and Event Start

| True Cycle | Daily Max (F) | Start Time (3 Hour Event)* | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 12 PM | 1 PM | 2 PM | 3 PM | 4 PM | 5 PM | 6 PM |
| 50 | 74 | -0.07 | -0.08 | -0.09 | -0.10 | -0.10 | -0.10 | -0.10 |
| | 76 | -0.09 | -0.12 | -0.14 | -0.15 | -0.15 | -0.14 | -0.13 |
| | 78 | -0.10 | -0.13 | -0.15 | -0.17 | -0.17 | -0.16 | -0.14 |
| | 80 | -0.13 | -0.17 | -0.20 | -0.22 | -0.22 | -0.20 | -0.18 |
| | 82 | -0.17 | -0.21 | -0.25 | -0.28 | -0.28 | -0.26 | -0.23 |
| | 84 | -0.21 | -0.27 | -0.31 | -0.33 | -0.33 | -0.30 | -0.26 |
| | 86 | -0.27 | -0.33 | -0.37 | -0.39 | -0.39 | -0.36 | -0.31 |
| | 88 | -0.32 | -0.39 | -0.43 | -0.46 | -0.45 | -0.41 | -0.35 |
| | 90 | -0.37 | -0.44 | -0.49 | -0.51 | -0.50 | -0.46 | -0.39 |
| | 92 | -0.44 | -0.52 | -0.56 | -0.58 | -0.56 | -0.51 | -0.43 |
| | 94 | -0.48 | -0.56 | -0.61 | -0.63 | -0.62 | -0.57 | -0.48 |
| | 96 | -0.55 | -0.64 | -0.69 | -0.71 | -0.70 | -0.64 | -0.54 |
| | 98 | -0.58 | -0.68 | -0.74 | -0.76 | -0.75 | -0.69 | -0.58 |
| | 100 | -0.65 | -0.77 | -0.84 | -0.87 | -0.85 | -0.76 | -0.64 |
| | 102 | -0.65 | -0.76 | -0.84 | -0.89 | -0.88 | -0.82 | -0.69 |
| 64 | 74 | -0.07 | -0.08 | -0.08 | -0.09 | -0.09 | -0.09 | -0.09 |
| | 76 | -0.10 | -0.11 | -0.13 | -0.14 | -0.14 | -0.13 | -0.12 |
| | 78 | -0.10 | -0.12 | -0.14 | -0.15 | -0.15 | -0.14 | -0.13 |
| | 80 | -0.14 | -0.17 | -0.19 | -0.20 | -0.20 | -0.19 | -0.18 |
| | 82 | -0.18 | -0.22 | -0.24 | -0.26 | -0.26 | -0.25 | -0.22 |
| | 84 | -0.25 | -0.29 | -0.32 | -0.33 | -0.33 | -0.31 | -0.28 |
| | 86 | -0.33 | -0.38 | -0.41 | -0.43 | -0.42 | -0.40 | -0.36 |
| | 88 | -0.44 | -0.49 | -0.52 | -0.54 | -0.53 | -0.51 | -0.46 |
| | 90 | -0.51 | -0.57 | -0.61 | -0.62 | -0.62 | -0.59 | -0.53 |
| | 92 | -0.64 | -0.70 | -0.74 | -0.75 | -0.73 | -0.69 | -0.63 |
| | 94 | -0.76 | -0.83 | -0.87 | -0.88 | -0.87 | -0.83 | -0.76 |
| | 96 | -0.90 | -0.98 | -1.02 | -1.04 | -1.03 | -0.98 | -0.90 |
| | 98 | -0.99 | -1.07 | -1.12 | -1.14 | -1.13 | -1.08 | -0.98 |
| | 100 | -1.21 | -1.32 | -1.38 | -1.40 | -1.38 | -1.31 | -1.19 |
| | 102 | -1.25 | -1.36 | -1.42 | -1.46 | -1.46 | -1.40 | -1.28 |
| 100 | 74 | -0.20 | -0.24 | -0.26 | -0.28 | -0.29 | -0.28 | -0.27 |
| | 76 | -0.27 | -0.33 | -0.37 | -0.40 | -0.40 | -0.38 | -0.35 |
| | 78 | -0.29 | -0.35 | -0.41 | -0.44 | -0.44 | -0.42 | -0.38 |
| | 80 | -0.37 | -0.45 | -0.51 | -0.55 | -0.55 | -0.52 | -0.47 |
| | 82 | -0.45 | -0.55 | -0.63 | -0.67 | -0.67 | -0.64 | -0.57 |
| | 84 | -0.57 | -0.67 | -0.75 | -0.78 | -0.78 | -0.73 | -0.65 |
| | 86 | -0.70 | -0.81 | -0.88 | -0.91 | -0.91 | -0.85 | -0.76 |
| | 88 | -0.83 | -0.94 | -1.01 | -1.04 | -1.03 | -0.98 | -0.87 |
| | 90 | -0.93 | -1.05 | -1.12 | -1.15 | -1.13 | -1.07 | -0.96 |
| | 92 | -1.07 | -1.19 | -1.26 | -1.27 | -1.25 | -1.16 | -1.04 |
| | 94 | -1.17 | -1.29 | -1.36 | -1.38 | -1.37 | -1.29 | -1.17 |
| | 96 | -1.30 | -1.43 | -1.50 | -1.53 | -1.51 | -1.43 | -1.29 |
| | 98 | -1.38 | -1.51 | -1.59 | -1.62 | -1.60 | -1.51 | -1.36 |
| | 100 | -1.54 | -1.69 | -1.77 | -1.81 | -1.78 | -1.67 | -1.50 |
| | 102 | -1.54 | -1.69 | -1.79 | -1.84 | -1.84 | -1.75 | -1.59 |

*Estimates exclude 30 minute phase in period and reflect the average reduction expected for the event

Table B-4: Four Hour Event Per Device Demand Impacts by Cycling Strategy, Temperature, and Event Start

| True Cycle | Daily Max (F) | Start Time (4 Hour Event)* | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 12 PM | 1 PM | 2 PM | 3 PM | 4 PM | 5 PM | 6 PM |
| 50 | 74 | -0.07 | -0.08 | -0.09 | -0.10 | -0.10 | -0.10 | -0.09 |
| | 76 | -0.10 | -0.12 | -0.14 | -0.14 | -0.14 | -0.13 | -0.12 |
| | 78 | -0.11 | -0.13 | -0.15 | -0.16 | -0.16 | -0.15 | -0.13 |
| | 80 | -0.14 | -0.17 | -0.20 | -0.21 | -0.20 | -0.18 | -0.16 |
| | 82 | -0.18 | -0.22 | -0.25 | -0.26 | -0.26 | -0.23 | -0.20 |
| | 84 | -0.23 | -0.27 | -0.30 | -0.31 | -0.30 | -0.27 | -0.23 |
| | 86 | -0.28 | -0.33 | -0.36 | -0.37 | -0.36 | -0.32 | -0.27 |
| | 88 | -0.34 | -0.39 | -0.42 | -0.43 | -0.41 | -0.37 | -0.31 |
| | 90 | -0.38 | -0.44 | -0.48 | -0.48 | -0.46 | -0.41 | -0.35 |
| | 92 | -0.45 | -0.52 | -0.55 | -0.54 | -0.51 | -0.45 | -0.38 |
| | 94 | -0.49 | -0.56 | -0.59 | -0.60 | -0.57 | -0.50 | -0.42 |
| | 96 | -0.56 | -0.63 | -0.67 | -0.67 | -0.64 | -0.57 | -0.47 |
| | 98 | -0.60 | -0.68 | -0.72 | -0.72 | -0.69 | -0.61 | -0.51 |
| | 100 | -0.68 | -0.77 | -0.82 | -0.82 | -0.77 | -0.67 | -0.55 |
| | 102 | -0.67 | -0.77 | -0.83 | -0.85 | -0.81 | -0.72 | -0.60 |
| 64 | 74 | -0.07 | -0.08 | -0.08 | -0.09 | -0.09 | -0.09 | -0.08 |
| | 76 | -0.10 | -0.12 | -0.13 | -0.13 | -0.13 | -0.13 | -0.12 |
| | 78 | -0.11 | -0.13 | -0.14 | -0.14 | -0.14 | -0.14 | -0.12 |
| | 80 | -0.15 | -0.17 | -0.19 | -0.19 | -0.19 | -0.18 | -0.16 |
| | 82 | -0.19 | -0.22 | -0.24 | -0.25 | -0.25 | -0.23 | -0.21 |
| | 84 | -0.26 | -0.29 | -0.31 | -0.32 | -0.31 | -0.29 | -0.26 |
| | 86 | -0.35 | -0.38 | -0.41 | -0.41 | -0.40 | -0.37 | -0.34 |
| | 88 | -0.45 | -0.49 | -0.52 | -0.52 | -0.51 | -0.47 | -0.43 |
| | 90 | -0.53 | -0.58 | -0.60 | -0.61 | -0.59 | -0.55 | -0.50 |
| | 92 | -0.65 | -0.70 | -0.73 | -0.72 | -0.70 | -0.65 | -0.58 |
| | 94 | -0.78 | -0.83 | -0.86 | -0.86 | -0.84 | -0.78 | -0.71 |
| | 96 | -0.92 | -0.98 | -1.02 | -1.02 | -0.99 | -0.92 | -0.84 |
| | 98 | -1.01 | -1.08 | -1.12 | -1.12 | -1.09 | -1.01 | -0.92 |
| | 100 | -1.24 | -1.33 | -1.37 | -1.37 | -1.33 | -1.24 | -1.11 |
| | 102 | -1.28 | -1.37 | -1.42 | -1.44 | -1.41 | -1.32 | -1.20 |
| 100 | 74 | -0.22 | -0.25 | -0.27 | -0.28 | -0.28 | -0.27 | -0.26 |
| | 76 | -0.30 | -0.35 | -0.38 | -0.39 | -0.39 | -0.37 | -0.34 |
| | 78 | -0.32 | -0.37 | -0.42 | -0.43 | -0.42 | -0.40 | -0.36 |
| | 80 | -0.41 | -0.48 | -0.53 | -0.54 | -0.53 | -0.49 | -0.44 |
| | 82 | -0.50 | -0.58 | -0.64 | -0.66 | -0.65 | -0.60 | -0.53 |
| | 84 | -0.62 | -0.70 | -0.76 | -0.77 | -0.75 | -0.69 | -0.60 |
| | 86 | -0.74 | -0.84 | -0.89 | -0.90 | -0.87 | -0.80 | -0.71 |
| | 88 | -0.88 | -0.97 | -1.02 | -1.03 | -1.00 | -0.92 | -0.82 |
| | 90 | -0.98 | -1.08 | -1.13 | -1.13 | -1.09 | -1.01 | -0.90 |
| | 92 | -1.12 | -1.22 | -1.26 | -1.25 | -1.20 | -1.10 | -0.98 |
| | 94 | -1.22 | -1.32 | -1.37 | -1.37 | -1.32 | -1.22 | -1.09 |
| | 96 | -1.36 | -1.46 | -1.51 | -1.51 | -1.46 | -1.35 | -1.20 |
| | 98 | -1.43 | -1.54 | -1.60 | -1.60 | -1.54 | -1.43 | -1.27 |
| | 100 | -1.60 | -1.72 | -1.78 | -1.78 | -1.71 | -1.58 | -1.40 |
| | 102 | -1.61 | -1.74 | -1.80 | -1.83 | -1.78 | -1.65 | -1.48 |

*Estimates exclude 30 minute phase in period and reflect the average reduction expected for the event

Table B-5: Five Hour Event Per Device Demand Impacts by Cycling Strategy, Temperature, and Event Start

| True Cycle | Daily Max (F) | Start Time (5 Hour Event)* | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 12 PM | 1 PM | 2 PM | 3 PM | 4 PM | 5 PM | 6 PM |
| | 74 | -0.07 | -0.08 | -0.09 | -0.09 | -0.09 | -0.09 | -0.09 |
| | 76 | -0.10 | -0.12 | -0.13 | -0.13 | -0.13 | -0.12 | -0.11 |
| | 78 | -0.11 | -0.13 | -0.14 | -0.15 | -0.14 | -0.13 | -0.12 |
| | 80 | -0.15 | -0.17 | -0.19 | -0.19 | -0.18 | -0.17 | -0.14 |
| | 82 | -0.19 | -0.22 | -0.24 | -0.24 | -0.23 | -0.21 | -0.18 |
| | 84 | -0.23 | -0.27 | -0.29 | -0.29 | -0.27 | -0.24 | -0.20 |
| | 86 | -0.29 | -0.33 | -0.35 | -0.34 | -0.32 | -0.28 | -0.24 |
| 50 | 88 | -0.34 | -0.39 | -0.41 | -0.40 | -0.37 | -0.33 | -0.28 |
| | 90 | -0.39 | -0.44 | -0.46 | -0.45 | -0.41 | -0.36 | -0.31 |
| | 92 | -0.46 | -0.50 | -0.52 | -0.50 | -0.46 | -0.40 | -0.33 |
| | 94 | -0.50 | -0.55 | -0.57 | -0.55 | -0.51 | -0.45 | -0.37 |
| | 96 | -0.56 | -0.62 | -0.64 | -0.62 | -0.57 | -0.50 | -0.41 |
| | 98 | -0.60 | -0.67 | -0.69 | -0.67 | -0.62 | -0.54 | -0.44 |
| | 100 | -0.68 | -0.76 | -0.78 | -0.76 | -0.69 | -0.59 | -0.48 |
| | 102 | -0.68 | -0.76 | -0.80 | -0.79 | -0.73 | -0.63 | -0.52 |
| | 74 | -0.07 | -0.08 | -0.08 | -0.08 | -0.08 | -0.08 | -0.08 |
| | 76 | -0.11 | -0.12 | -0.13 | -0.13 | -0.13 | -0.12 | -0.11 |
| | 78 | -0.11 | -0.13 | -0.14 | -0.14 | -0.13 | -0.13 | -0.12 |
| | 80 | -0.16 | -0.17 | -0.19 | -0.19 | -0.18 | -0.17 | -0.15 |
| | 82 | -0.20 | -0.22 | -0.24 | -0.24 | -0.23 | -0.21 | -0.19 |
| | 84 | -0.27 | -0.29 | -0.31 | -0.31 | -0.29 | -0.27 | -0.24 |
| | 86 | -0.35 | -0.38 | -0.40 | -0.40 | -0.38 | -0.35 | -0.31 |
| 64 | 88 | -0.46 | -0.49 | -0.51 | -0.50 | -0.48 | -0.44 | -0.40 |
| | 90 | -0.54 | -0.58 | -0.59 | -0.58 | -0.56 | -0.51 | -0.46 |
| | 92 | -0.66 | -0.70 | -0.71 | -0.70 | -0.66 | -0.61 | -0.54 |
| | 94 | -0.79 | -0.83 | -0.84 | -0.83 | -0.79 | -0.73 | -0.66 |
| | 96 | -0.93 | -0.98 | -1.00 | -0.98 | -0.94 | -0.87 | -0.78 |
| | 98 | -1.02 | -1.08 | -1.10 | -1.08 | -1.03 | -0.95 | -0.86 |
| | 100 | -1.26 | -1.33 | -1.34 | -1.32 | -1.26 | -1.16 | -1.04 |
| | 102 | -1.30 | -1.37 | -1.40 | -1.39 | -1.33 | -1.24 | -1.11 |
| | 74 | -0.23 | -0.26 | -0.27 | -0.28 | -0.27 | -0.27 | -0.26 |
| | 76 | -0.32 | -0.36 | -0.38 | -0.38 | -0.38 | -0.36 | -0.33 |
| | 78 | -0.34 | -0.39 | -0.42 | -0.42 | -0.41 | -0.38 | -0.34 |
| | 80 | -0.44 | -0.50 | -0.53 | -0.53 | -0.50 | -0.47 | -0.41 |
| | 82 | -0.54 | -0.61 | -0.64 | -0.64 | -0.61 | -0.56 | -0.49 |
| | 84 | -0.65 | -0.72 | -0.76 | -0.75 | -0.71 | -0.64 | -0.56 |
| | 86 | -0.78 | -0.85 | -0.89 | -0.88 | -0.83 | -0.75 | -0.66 |
| 100 | 88 | -0.91 | -0.99 | -1.02 | -1.00 | -0.95 | -0.87 | -0.77 |
| | 90 | -1.02 | -1.09 | -1.12 | -1.10 | -1.04 | -0.95 | -0.84 |
| | 92 | -1.16 | -1.23 | -1.24 | -1.21 | -1.14 | -1.03 | -0.91 |
| | 94 | -1.26 | -1.33 | -1.36 | -1.33 | -1.26 | -1.15 | -1.02 |
| | 96 | -1.39 | -1.47 | -1.50 | -1.47 | -1.39 | -1.27 | -1.13 |
| | 98 | -1.47 | -1.56 | -1.58 | -1.55 | -1.47 | -1.34 | -1.20 |
| | 100 | -1.64 | -1.74 | -1.76 | -1.73 | -1.63 | -1.48 | -1.32 |
| | 102 | -1.66 | -1.76 | -1.80 | -1.78 | -1.70 | -1.56 | -1.38 |

*Estimates exclude 30 minute phase in period and reflect the average reduction expected for the event